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THE ADOPTION-SUBSTITUTION GAP:
ADMINISTRATIVE EVIDENCE FROM SWEDISH E-BIKE SUBSIDIES

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ABSTRACT

Policymakers increasingly use green subsidies to advance Sustainable Development Goals (SDGs) related to climate, mobility, and health. These programs assume a causal chain: subsidies drive technology adoption, which induces behavioral substitution that then generates sustainability impact. We test this mechanism in the context of a nationwide e-bike subsidy program in Sweden, focusing on the adoption-substitution gap—the friction between acquiring green technology and displacing high-carbon behaviors. Linking administrative data on all 90,000 recipients to vehicle registry and insurance records, we find that while the subsidy successfully doubled e-bike sales with complete price pass-through, behavioral substitution was minimal. Objective vehicle-kilometers traveled (VKT) changed marginally, leading to negligible emissions reductions and health gains. Notably, survey-based substitution estimates within the same population substantially overstate realized reductions, suggesting a reporting bias in stated-preference data. Our findings highlight the necessity of targeting green subsidies toward populations whose behavior is most elastic to ensure cost-effective climate and mobility outcomes.

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1 Introduction

Governments worldwide are expanding the use of green subsidies to accelerate progress toward the United Nations Sustainable Development Goals (SDGs). Many programs aim to support climate mitigation (SDG 13), promote healthier and more active lifestyles (SDG 3), and improve urban mobility (SDG 11). A common conceptual model underlies these initiatives: subsidies increase the *adoption* of green technologies; adoption induces *behavioral change*; and behavioral change produces *sustainability impact*. Figure 1 summarizes this conceptual structure.

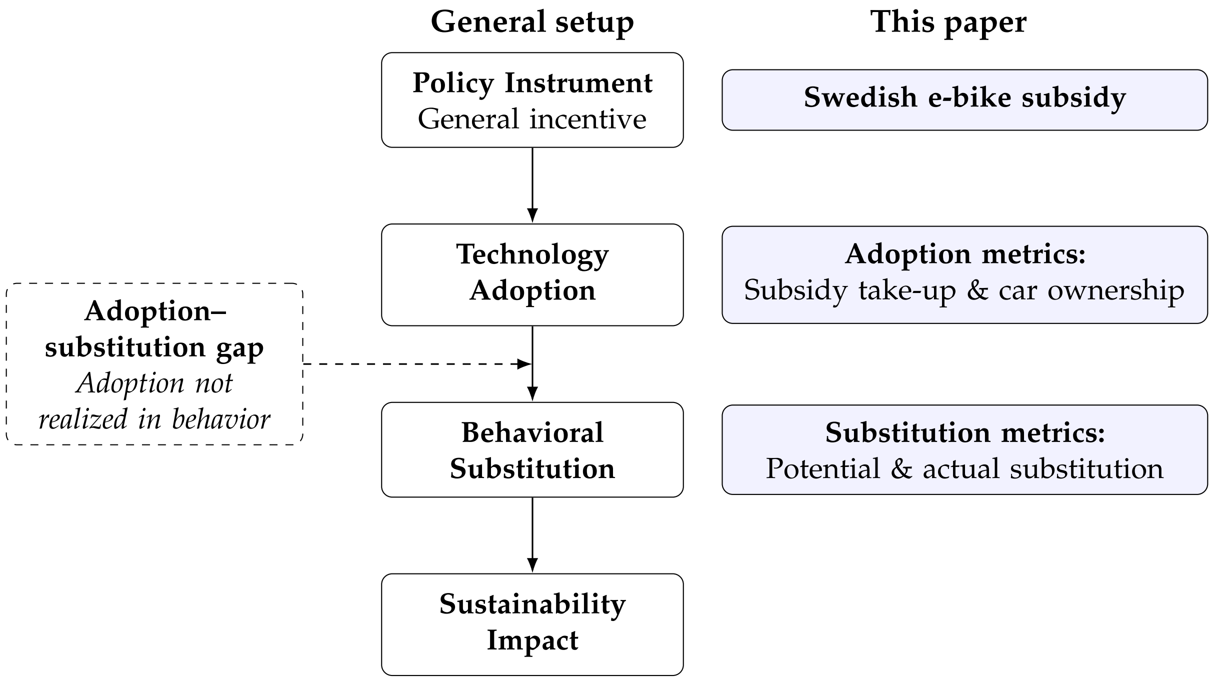
In practice, however, a significant friction often emerges between the first and second steps of this chain—a phenomenon we define as the adoption-substitution gap. While subsidies are highly effective at incentivizing technology acquisition, the degree to which these new assets actually displace ”brown” behaviors (such as internal combustion engine travel) is often unknown. If a green technology serves as a recreational complement to an existing fleet rather than a utility substitute, the link between adoption and impact breaks down. Historically, quantifying this gap has been hindered by a reliance on structural simulations or self-reported survey data, which is prone to social desirability bias. Without objective, population-scale evidence on the behavioral margin, the true welfare gains of green subsidies remain speculative.

Electric bicycles (e-bikes) offer an unusually clean context in which to study this mechanism directly. Nearly all of their sustainability benefits—reduced emissions, congestion relief, and increased physical activity—arise only when e-bike trips *replace* car trips. Unlike electric vehicles or solar panels, which can generate some benefits independently of behavioral shifts, e-bike subsidies rely almost entirely on behavioral substitution for their impact. This makes the e-bike an ideal ”laboratory” setting to evaluate whether green-technology adoption translates into meaningful behavioral change.

In this paper, we evaluate a large-scale e-bike subsidy program implemented in Sweden in 2018. We make a distinct methodological contribution by linking the universe of 90,000 subsidy recipients to administrative vehicle registry and insurance records. This allows us to move beyond stated intentions and observe the true vehicle-kilometers traveled (VKT) at a population scale. By comparing these administrative records to SEPA-commissioned survey data within the same population, we are able to quantify the magnitude of the reporting bias that often inflates the perceived efficacy of green mobility programs.

Figure 1: Conceptual Framework for Green Subsidies

This figure visualizes the conceptual framework for green subsidies as a two-step process. General factors influence adoption and substitution. Subsidy programs affect adoption, which together with behavioral substitution, determines sustainability impacts.



To start, we find that the subsidy led to a surge in e-bike adoption, with the fiscal incentive completely passed through to consumers. Furthermore, two-thirds of recipients report the subsidy was ”decisive” for their adoption, suggesting high policy additionality. However, despite this successful adoption, we find that behavioral substitution is minimal. Car ownership remains unchanged, and realized reductions in driving are small—representing only a fraction of what is suggested by survey-based and hypothetical benchmarks.

Our findings suggest that the program generated limited emissions reductions and modest health gains because the technology functioned largely as a fleet addition for many households. However, counterfactual targeting analyses reveal that this gap is not inevitable; if car owners fully substitute their commuting to e-biking this would yield substantially larger reductions in driving. Our results highlight the importance of aligning SDG-oriented subsidies with populations whose behavior is most elastic, and caution against relying on adoption metrics or survey data as proxies for sustainability impact.

Related literature and contribution. Our paper contributes to three primary strands of literature concerning the effectiveness and design of green subsidies. Specifically, we address the mechanisms of behavioral substitution, the methodological challenges of measuring policy impact, and the optimal targeting of fiscal incentives.

First, we provide empirical evidence on the adoption-substitution gap—the friction between the acquisition of a "green" technology and the displacement of a "brown" activity. While a vast literature focuses on the drivers of technology adoption (see, e.g. De Groote and Verboven (2019)), far less is known about the subsequent behavioral margin. In the vehicle market, Xing, Leard, and Li (2021) use structural modeling to show that electric vehicle (EV) subsidies often result in "fleet expansion" rather than the retirement of high-emission vehicles.

We extend this inquiry to micromobility, where the sustainability impact depends almost entirely on physical behavioral substitution. Unlike energy-efficient appliances or EVs, which may yield passive savings regardless of usage intensity, e-bikes require an active shift in travel habits to generate benefits. Our findings suggest that in the absence of high baseline car-dependence, e-bikes act more as recreational complements than utility substitutes, mirroring the "rebound effects" documented in other energy sectors (Sorrell, Dimitropoulos, and Sommerville (2009), Gillingham, Rapson, and Wagner (2016)).

Second, we contribute to the methodological debate on how behavioral shifts are measured. Environmental policy evaluations frequently rely on self-reported survey data, which are susceptible to social desirability bias and hypothetical bias (Kollmuss and Agyeman (2002), ElHaffar, Durif, and Dubé (2020)). By linking the universe of subsidy recipients to administrative vehicle registries, we move beyond stated intentions to observe "revealed" driving behavior.

This aligns our work with a growing movement in environmental economics to use high-frequency, objective data—such as residential billing records in energy efficiency studies (Fowlie, Greenstone, and Wolfram (2018))—to benchmark policy performance. Our study is unique in that it directly compares administrative records with survey-based estimates within the same population, allowing us to quantify the specific magnitude of reporting bias that often inflates the perceived efficacy of green mobility programs.

Finally, we contribute to the literature on the additionality and targeting of fiscal incentives. A persistent concern in subsidy design is the "windfall" gain to inframarginal buyers—those who would have adopted the technology even without the incentive (Boomhower and Davis (2014)). While we find that the Swedish subsidy had relatively high additionality, this adoption did not translate into high social returns.

This introduces a "Targeting Paradox": patterns of subsidy adoption do not systematically align with patterns of behavioral substitution. Across multiple dimensions, high levels of subsidy take-up, car ownership, and pre-subsidy driving do not reliably translate into greater post-subsidy substitution. This disconnect between adoption and behavioral response suggests that green subsidies are most cost-effective when targeted to underlying behaviors and constraints rather than applied uniformly (Allcott and Knittel (2015), Knittel and Li (2024)).

The remainder of the papers is organized as follows. Section 2 explains the subsidy and how we combine the various data sources for the analysis. Section 3 presents the results on adoption and Section 4 on substitution from driving. We consider effects on health, congestion and carbon emissions in Section 5. Section 6 presents a cost-benefit analysis of the program using different methods of measurement including counterfactuals. Section 7 concludes.

2 Background and Data

This section first describes the Swedish e-bike subsidy program and situates it in the context of similar subsidy schemes implemented internationally. We then present the e-bike sales and subsidy data obtained from the Swedish Environmental Protection Agency (EPA) and Solid. Finally, we describe the matched car ownership records for subsidy recipients, as well as the survey data covering a subsample of individuals who received the subsidy.

2.1 The Swedish E-bike Subsidy

On September 20, 2017, the Swedish government led by a red-green minority coalition consisting of the Green Party and Social Democrats announced a scheme to increase green transportation through a subsidy of e-bikes. The aim of the subsidy was to improve conditions for climate-smart transportation and to contribute to improved public health. The program was formally in place on February 1 of 2018 but allowed consumers to retroactively apply for the subsidy from the date of announcement. The Swedish government's original plan, to be implemented by SEPA, was to spend approximately one billion Krona ($113 million) on e-bike subsidies over a three year period from 2018 to 2020. According to the scheme, an e-bike consumer could get a subsidy of 25 percent of the purchasing price with an upper limit of 10,000 Kronas, corresponding to around $1,100. Hence, the policy targeted purchases only; there were no requirements on effective use or car ownership.

To claim the subsidy, individuals were acquired to fill out a detailed form online or by regular mail. In addition to personal details, the form included information on bike and model as well as the retailer selling the bike and the receipt of purchase. The claimants were required to be at least 18 years of age, and restricted to only one purchase. The program covered only new pedelecs and excluded smaller electrical vehicles (e.g. hoverboards, scooters and Segways) but did include bigger ones, such as quadri-cycles and cargo bikes provided that they fulfilled the European Electrically Powered Assisted Cycles (EPAC) standard.

Due to exceptionally high demand, the money budgeted for 2018 did not last the entire year. The pace at which people wanted to claim the subsidy was deemed unsustainable given the allocated resources. In July 2018, 45 million Kronas was added. And in September 2018, an additional 40 million Kronas intended for the 2019 subsidy program were moved to the 2018 program. On October 18 in 2018, the program was ended prematurely due to its popularity after having used a total of 425 million Kronas ($48 million). Any e-bikes sold after this date were no longer eligible to receive the subsidy.

The subsidy was not extended. The elections in the fall of 2018 gave no stable parliament majority. The center-right opposition was skeptical of the subsidy program—viewing it as inefficient use of tax money. The red-green government proposed to continue the program in 2019. The result of the post-election negotiations was that the red-green government remained in place, but an opposition budget for 2019 passed in parliament with a budget that did not include funds for a continuation of the e-bike subsidy program.

2.2 Similarity to E-bike Subsidies Around the World

E-bike subsidies similar to the Swedish program have been widely implemented across Europe and North America. According to the European Cyclists' Federation (ECF), more than 300 tax incentives and purchase-premium schemes for cycling were in place across Europe at the national, regional, and local levels by the end of 2021, with the explicit aim of encouraging cycling and reducing car use. While many of these incentives were introduced over the past decade, their number increased markedly after 2019.

In the United States, a federal e-bike subsidy was proposed during the Biden administration through H.R. 1019, the "Electric Bicycle Incentive Kickstart for the Environment Act," which would introduce a 30% tax credit for e-bike purchases. At the same time, a range of state- and city-level incentive programs are already in operation. In Germany, the Green Party has proposed large-scale support for cargo bicycles, with planned subsidies totaling up to one billion Euros over the next legislative period.

Table I provides a selective overview of prominent e-bike incentive programs that are currently in place, or have recently been implemented, throughout the world.[1] When comparing the Swedish program to these existing subsidies, three features stand out.

First, a capped discount targeted directly towards consumers, like in Sweden, is according to our investigation by far the most popular type of intervention, followed by tax credits and flat rates that sometimes are also combined with scrapping a fossil fuel vehicle (known as "Cash-for-Clunkers" programs, Mian and Sufi (2012)). To the extent

[1] See, for example, McQueen, MacArthur, and Cherry (2019) and Newson and Sloman (2019) for earlier overviews. The European Cyclists' Federation maintains a comprehensive and regularly updated overview of European cycling incentives at `https://ecf.com/resources/financial-incentives`.

Table I: Subsidy Programs

This table reports a non-exhaustive list of e-bike subsidy programs across the world divided into programs on the national and regional level. We report type of subsidy, discount level, target of the discount, the maximum funding (if any) of the incentive, total earmarked funds (if any) of the whole program, number of participants and a short remark where applicable. The data of this table has been acquired from various online sources, including the European Cyclists' Federation (EFC).

Panel A: E-bike Programs

Location	Type*	Discount	Target**	Max. funding	Tot. earmarked	Period	Participation	Requirements/ Remarks
National programs								
Sweden	D	25%	C	$1,100	$48 mn	2017-2018	97,000	$113 mn planned 2018-2020
China	D	15%	C	$70	n/a	2024-2025	1.38 mn in 2024	Trade-in scheme. Extended in 2025.
India	D	$70/kWh battery	C	15% factory price	$90 mn	2024-2025	est. 0.5 mn in 2024	Part of EMPS. Extended in 2025.
United States	TC	30%	C	$1,500	$4.1 bn		n/a	Proposed E-BIKE Act.
Austria	D	25%	B	€300	>€1 bn	2016-2023, 2025	n/a	
France	D	40%	C	€400	n/a	2017-2027	n/a	Max €2,000 for cargo bikes.
Germany	D	25%	C	€2,500	€1 bn	2024	n/a	Suspended in 2024 due to budget freeze.
Italy	D	70%	C	€500	€125 mn	2020-2022	n/a	E-bikes, E-scooters, sharing services.
Regional programs								
Delhi, India	D	$60/kWh battery	C	$360	n/a	2025	n/a	
Maharashtra, India	D	$120/kWh battery	C	$240	n/a	2025	n/a	50% road tax exemption.
Oslo, Norway	D	25%	C	$600-$1,200	$1.2 mn	2016-2020	1,000-2,000	E-bikes/Cargo bikes.
British Columbia, CAN	FR	$850 (CAD)	C	$1,000 (CAD)	n/a	2019-	n/a	Mandatory car replacement.
California State, US	D	n/a	C	n/a	$10 mn	2020-	n/a	CalBike and California Air Resources Board.
Rome, Italy	D		C	€500	n/a	2020	est. 50,000	Bikes and e-scooters.

Panel B: Commuting Fiscal Policies

Location	Type*	Amount	Target**	Max. funding	Mode neutral	Favored mode***	Effective use bike	Requirements/ Remarks
Sweden	TD	$0.25/km	C	n/a	No	PT/CA	No	Car distance > 5km & costs exceed $1,200.
Austria	B	€463	C	n/a	No	PT/CA	No	Higher if PT unreasonable or unavailable.
Belgium	R	%75	C	€2,500	No	PT	Yes	
Denmark	TD	€0.27/km	C	n/a	Yes	n/a	Yes	Distance > 12km.
France	B	€500	C	n/a	No	CA/CY	No	Voluntary sustainability mobility bonus.
Germany	TD	€0.30/km	C	€4,500	Yes	n/a	Yes	> 20km: €0.38/km.
Netherlands	R	€0.23/km	C	n/a	Yes	n/a	Yes	Allowances can differ by mode.
United Kingdom	TC	25%-39%	C	n/a	No	CY	No	Cycle scheme, 25%-39% tax break.

*) Type of fiscal policy where (B) denotes tax-free bonus or contribution, (D) discount proportional to price, (FR) flat rate per unit, (L) government loans, (R) tax-free reimbursement, (TC) tax credit, and (TD) tax deduction.
**) Target for subsidy where (C) denotes individual consumers and (B) denotes businesses.
***) Favored mode of fiscal policies where (CY) denotes cycling, (CA) denotes car driving, and (PT) denotes public transport.

other programs in the world are similar in structure, we believe that our results should be transportable.

Second, the size of Sweden's program is substantial in comparison with others that are currently in place. But there are even larger programs going forward. The €1 billion program proposed by the Green Party in Germany and the $4.1 billion E-BIKE bill in the US shows that subsidies of e-bikes are likely not only here to stay, but become part of general policies to steer households towards green transportation.

Finally, the available documentation surrounding the conditions and take-up of the international programs is sparse, making it difficult to evaluate them. With more detailed data at hand, this paper aims to fill this gap.

In addition to e-bike subsidies, many European countries have extensive fiscal policies in place that target the costs of commuting. Panel B of Table I presents a summary some of them. These policies employ a direct monetary trade-off between commuting with cars, public transport, and bikes. Contribution schemes are often based on the effective use of transportation modes, not the purchase of vehicles.

However, there is some variation in how policies influence trade-offs between transportation modes. Some policies are mode neutral, while others favor specific modes of transport. In countries like Sweden and Austria, policies tend to favor commuting by car, as tax deductions are typically available only for driving (with limited exceptions for public transportation). A second group of countries, such as Denmark, the Netherlands and Germany, adopt a mode-neutral approach, offering equal tax deductions for all forms of transportation. Lastly, a few countries, including Belgium, France, and the United Kingdom, have introduced policies that specifically encourage environmentally friendly transportation options.

2.3 E-Bike Subsidy Data

We obtain the complete subsidy registry from SEPA containing 96,869 transactions, of which 89,621 correspond to regular pedelecs (e-bikes).[2] The average subsidy amounts to 4,113 SEK ($463).

The data contain detailed information on bikes, recipients, and retailers. For recipients, we observe zip code, age, income, education, marital status, and gender. For 31% of recipients, home and work coordinates are available, allowing us to compute the Euclidean home–work distance. Retailer data include corporate identity numbers and location: among the 1,578 retailers in the sample, one-third sold only a single e-bike, while the top 85 retailers account for two-thirds of total sales. Finally, for each bike we observe

[2] We exclude 7,248 transactions related to light mopeds, electric wheelchairs, other light electric vehicles, and roughly 800 e-bikes purchased abroad.

model, purchase price, and subsidy amount.

While the SEPA registry is detailed and comprehensive for subsidized purchases, we do not observe e-bike transactions outside the subsidy program.

2.4 Solid Insurance Data

In order to obtain estimates of pass-through, we need detailed data from outside the subsidy period. The Swedish Cycle Association (a trade organization) reports only aggregated data year-on-year defined from September to August, but shows a clear increase for the period of the subsidy. For the year 2016/2017 sales were 67,000 growing to 103,000 for the 2017/2018 period. This aggregation is based on data from importers for which there is no way to identify individual e-bike transactions, and the measured time period does not exactly coincide with the subsidy period.

Instead, our second e-bike data source comes from the insurance company Solid. An important business of Solid is to co-insure bikes. Even though all home insurance policies in Sweden also cover bikes, they are normally capped and come with substantial deductibles. Solid offers additional coverage for every new bike sold in its network of retailers, which customers can choose to extend after three months. The insurance policies are offered at purchase of new bikes through a network of bike retailers. Solid's customers include all major retailers specializing in bikes, and an estimated 50% of all bikes sold in Sweden are sold with a Solid insurance. When comparing retailers across the Solid data versus the SEPA data, retailers not attached to Solid are typically larger retailers who do not specialize in bikes (such as department stores and online-only retailers).

From Solid, we obtain bike brand, model and price, but also age, gender and zip-code by the insured, as well as corporate identity number and location of the retailer selling the bike; hence making it possible to merge the two data sets. The Solid data is of high quality with respect to brand, date, retailer and zip-code (due to standardized fields), but is of lower quality with respect to price and model which is sometimes missing, insufficient or unreasonable.

The full data set consists of almost 695,587 new bicycle purchases for the time period January 2017 to October 2019. From this data, we identify 91,506 e-bikes that we then seek to find which ones received a subsidy from the SEPA data. We find that 76% of all subsidized e-bikes were sold by stores affiliated with Solid.

2.5 Matching SEPA Subsidy to Solid Data

We apply a set of screens in order to obtain a match between the Solid and subsidy data sets that we restrict with respect to model names and retailers. The final regression sample contains 20,586 e-bikes consisting of 38 models sold by 49 retailers during 2017 to 2019 corresponding to 55% of the total number of e-bikes in the Solid sample.[3] We find that 75% of all bikes sold during the subsidy period obtained a subsidy. We are relatively confident that the remaining 25% of the e-bikes that did not receive a subsidy in the subsidy period is likely due to the customer not following SEPA procedures to claim their subsidy, chose not to do so or did not qualify. This could be for various reasons of which we can only speculate: purchase of a second e-bike or purchase on behalf of someone else, the customer is under the age of 18, failing to meet the filing procedure of sending in the original receipt, preferences or ignorance.

2.6 Merging E-Bike Subsidy Household to Car Registry Data

Statistics Sweden matches our sample of e-bike subsidy receivers to car registry records obtained from the Swedish Traffic Authority (STA) for the years straddling the subsidy. We find that 52,840 individuals (59%) in our e-bike data owned a car in this period which is close to the national average of 60%. Apart from car ownership the data contains details of type of car (i.e. Gasoline, Diesel, Hybrid-Electric or Electric) and year of make, making it possible to get a more precise estimate of carbon emissions. Most importantly, the data includes yearly kilometers driven which is our key measure VKT, Vehicle Kilometers Travelled, in the years 2016 to 2019.

We obtain a measure of commuting distance by drawing on a subset of 27,628 individuals for whom we have home and work coordinates. We calculate the Euclidian distance and find the mean (median) to be 21.03 kilometers (4.12 kilometers). Yearly commuting distance is estimated by scaling with commuting days across distances reported by the government agency Traffic Analysis (Trafikanalys (2020)).[4]

2.7 Survey Data

SEPA commissioned a research report, in which they invited a representative sample of 10,500 people from the subsidy-takers to take an online survey in March 2019. Details about sampling and survey instrument can be found in the SEPA report (Naturvårdsverket (2019)).[5] The survey contains questions about motives to buy the e-bike, commuting distance and means of transportation before and after the e-bike purchase. Around 3,500

[3]Details of this procedure is outlined in the appendix: 3,788 e-bikes were sold before, 10,576 were sold during, and 6,222 were sold after the subsidy was in place.

[4]This mainly adjusts for the fact that people with very long commuting distances typically commute fewer days.

[5]The technical report from Statistics Sweden documents that the survey sample is representative of the full subsidy sample and so sample weights were not computed. A copy of this report is available from the authors.

people answered the question about how important the subsidy was for their decision to buy an e-bike on the survey, but fewer reported how their travel behavior changed with respect to commuting.

Two survey questions allow us to pin down the impact of the purchase of an e-bike on commuting modes. The first question is about the distance to work, and the second how many weekly trips you make with each mode of transportation for this commute. Of the 3,523 households that took the survey, 2,195 reported that they used the e-bike for commuting along with commuting distance, where 1,944 also reported their means of transportation (car, public transportation, walking or regular bicycle)—separately for winter and summer before and after the purchase of the e-bike.[6] We use the survey to infer the self-reported use of e-bikes in substituting for car driving before and after the purchase. As surveys have been the primary source of estimating the substitution between driving and biking across existing research, the intersection of registry and survey data provides us with an opportunity to investigate discrepancies between the self-reported and recorded driving reductions.

3 E-Bike Adoption

In this section, we show the following: (1) the e-bike subsidy was highly effective in promoting e-bike adoption, (2) that this is consistent with high degree of pass-through of the subsidy to consumers, (3) a substantial fraction of subsidy recipients (two-thirds) report that the generosity of the subsidy played an important role in their adoption decision, and (4) the subsidy recipients were older and had higher incomes than the general population, but were no more likely to own a car.

3.1 Sales over Time

First, we show that e-bike sales spiked during the period of the subsidy. Figure 2 provides a graphical representation of e-bikes sold over time for the top models and retailers that we match across the subsidy and insurance sample described in Section 2.5. The plot shows the e-bikes sold before, during, and after the subsidy in which we highlight the subsidy period in darker color. Monthly transactions during the subsidy period are around 1.7 times higher than those outside the subsidy period which corresponds well with the spike in aggregate sales.

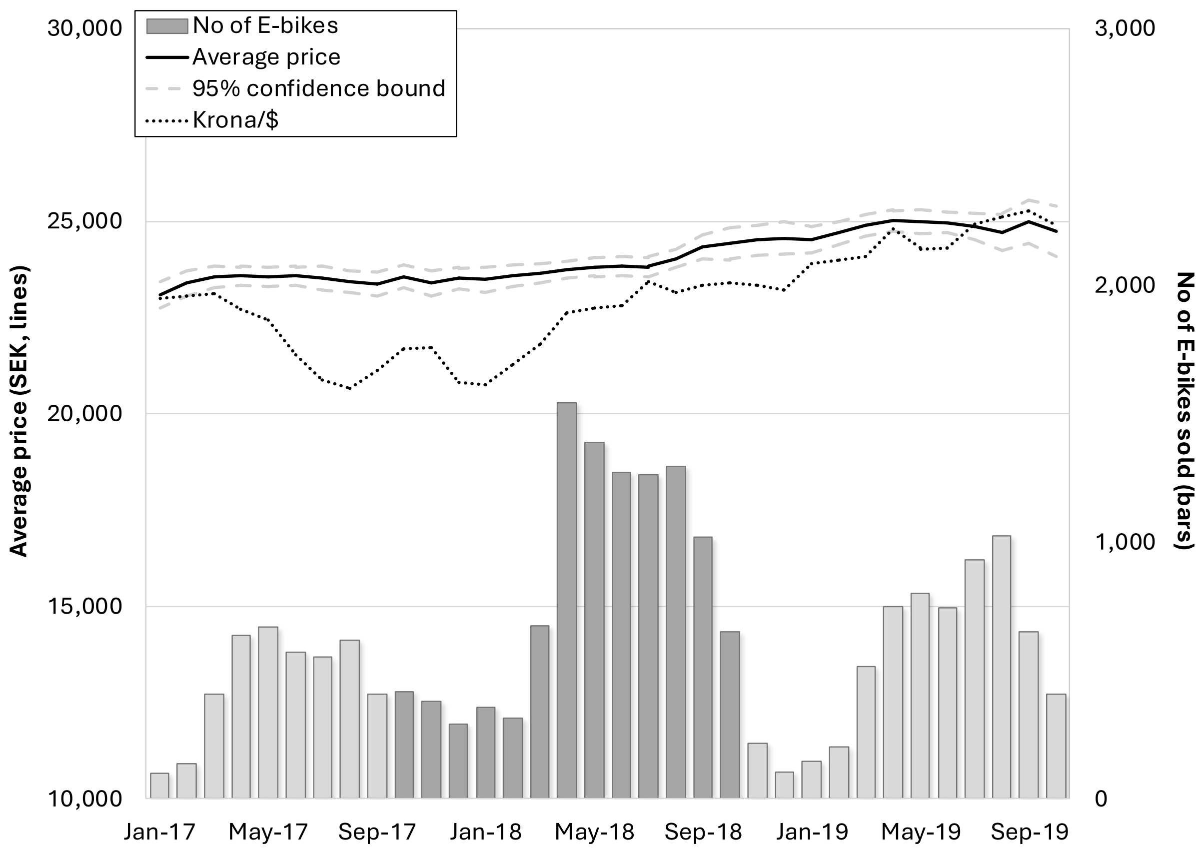
We also trace out the average price for bikes, in which we hold model and retailer constant throughout. Although the average price of the e-bikes have been rising from

[6]The relatively extensive amount of information that was to be provided likely contributed to the lower response rate for these items of the survey.

23,000 Kronas ($2,600) to almost 25,000 Kronas ($2,800) at the end of the period, there is no sign of a sharp increase in prices as the subsidy was introduced. As e-bikes are mainly produced in China, and are subject to exchange rate conditions, we also plot the average Krona/$ exchange rate in Figure 2, which indicates that some of the price increase can be due to a weakening of the currency.

Figure 2: Matched E-bikes: Purchases and Average Price

This figure displays the number of sold e-bikes of the top selling 38 models sold through the largest 49 retailers during the sample period. Dark grey shaded bars indicate the subsidy period October 2017 to October 2018 (right scale). The solid line displays average price which is recovered from the pass-through regression in Table II (left scale) along with a 95% confidence interval indicated by dashed lines. There are 20,586 observations in total during the time period January 2017 to October 2019. The dotted line shows the Krona per dollar exchange rate which is normalized with the average bike price in January 2017.



3.2 *Pass-Through*

Second, we show that the subsidy was entirely passed through to consumers. Following Busse, Knittel, Silva-Risso, and Zettelmeyer (2012) and Busse, Silva-Risso, and Zettelmeyer (2006), we estimate a pass-through regression using e-bike model, retailer, county and time fixed effects.

Let $Subsidy_{i,j,t}$ be the size of the subsidy that consumer i received on her e-bike j

purchase at time t. $P_{i,j,r,t}$ be the price that consumer i pays for e-bike j from retailed r at time t net of the $Subsidy_{i,j,t}$. The pass-through regression is then given by:

$$P_{i,j,r,t} = \beta_0 + \beta_1 Subsidy_{i,j,t} + \beta_2 CustomerDemo_i + \beta_3 Krona/\$ + \delta_j + \kappa_r + \nu_t + \epsilon_{i,j,r,t} \quad (1)$$

$CustomerDemo_i$ is customer demographics including age and gender. Krona/$ is the Kronor per US dollar exchange rate to capture pricing effects associated with changes in exchange rates since the e-bikes are imported into Sweden. δ_j is e-bike brand and model fixed effect. Retailer fixed effects is denoted κ_r and ν_t is month times year fixed effects. The coefficient of interest is β_1. The null hypothesis of a full pass through of the subsidy to consumers means that $\beta_1 = -1$. If there is incomplete pass-through, then we expect a coefficient to be negative but smaller in absolute value than 1. That is, retailers are raising their prices for transactions where customers received a subsidy and not raising their prices where customers do not receive a subsidy.

The regression results are presented in Table II. In the first column, we report the results with just model fixed effects, which control for the impact of quality differences in e-bikes sold. We see that the coefficient of interest is -1.021 and highly statistically significant. It cannot be rejected from the null of complete pass-though ($\beta_1 = -1$). The p-value from a t-test that it differs from -1 is only moderately significant at 0.067. Customer demographics to age and gender have no statistical significance in this regression since they are mostly related to bike brand and model.

But the coefficient on Krona/$ is significantly positive. The coefficient of 946 means that a one Krona depreciation against the dollar means almost a 1,000 Kronor higher average price for e-bikes. This coefficient is capturing the fact that the Krona is weakening over this sample period, which makes imports more expensive. Hence retailers pass-through some of those costs to consumers (Goldberg and Hellerstein (2008), Nakamura (2008), Nakamura and Zerom (2010)). This can be seen in Figure 2, where we plot the average e-bike price using the black line. The lower and upper 95 percent confidence bounds are also reported. The Krona/$ time series is reported in the dotted line. One can see that there is trend increase in the average price. The USD relative to the Krona is also increasing starting in January 2018.

In column (2), we add time fixed effects instead of Krona/$ to capture exchange rate effects and also introduce retailer fixed effects. Our coefficient of interest is little changed as it decreases from -1.021 to -0.993. This -0.993 coefficient is also highly statistically significant but does not differ from the null hypothesis ($\beta_1 = -1$) with a p-value of 0.436. However, the retailer fixed effects are highly significant, consistent with the importance of retailer pricing or marketing heterogeneity in the context of e-bikes (Pless and van Benthem (2019)). In column (3), we also introduce county FE to account for the influence of

Table II: Subsidy Pass-Through Regressions

This table reports OLS regressions where the dependent variable is purchase price net of subsidy. The independent variables are the value of the subsidy, age, gender and the Krona to US dollar exchange rate. Fixed effects include e-bike model and retailer. Time fixed-effects in columns (2)-(3) replaces the currency time-series with fixed effects on a month-year frequency. Column (3) includes fixed effects for the county in which the consumer lives. The sample includes 20,586 e-bikes sold from January 2017 to November 2019 in total where 7,914 e-bikes were sold during the subsidy period between September 20, 2017 to October 18, 2018. The bottom row displays the rejection probability for a t-test that the subsidy coefficient is different from -1. Standard errors are clustered on retailers.

	Price net of subsidy		
VARIABLES	(1)	(2)	(3)
Subsidy	-1.021***	-0.993***	-0.994***
	(0.011)	(0.008)	(0.008)
Age	-0.815	-0.341	-0.424
	(1.546)	(0.635)	(0.606)
Female	18.722	13.477	13.850
	(20.826)	(14.237)	(14.365)
Krona/$	946.185***		
	(64.031)		
Constant	24,240.199***	23,081.882***	22,835.021***
	(346.211)	(516.237)	(536.280)
Observations	20,586	20,586	20,558
R-squared	0.905	0.934	0.934
Model FE	Yes	Yes	Yes
Time FE	No	Yes	Yes
Retailer FE	No	Yes	Yes
County FE	No	No	Yes
p-value Subsidy = -1	0.067	0.436	0.483

geographical heterogeneity on pass-through estimates. But the coefficient of interest is little changed moving from column (2) to column (3).

Our complete pass-through estimates are consistent with a spike in sales during subsidy period observed from the Figure 2, with the bars capturing the number of matched e-bikes sold each month. Recall that there were 10,576 e-bikes sold during the subsidy period (or 755 e-bikes per month) in our model/retailer restricted sample compared to 3,788 before the subsidy (or 420 e-bikes per month) and 6,222 after the subsidy (or 622 e-bikes per month). So, the marked increase in the sale of e-bikes during the subsidy period is consistent with the complete pass-through of the subsidy. Moreover, we note that e-bike sales after the subsidy were still higher than pre-subsidy levels. This might be due to indirect effects of the subsidy in spurring household adoption. We leave this conjecture for future investigation.

3.3 Importance of E-bike Subsides for Adoption

Third, many consumers were marginal in the sense that they would not have otherwise bought an e-bike without the subsidy. Although difficult to measure directly, this margin is critical for evaluating policy efficacy. We use follow-up survey data from SEPA to shed light on this issue. The survey asks: "How important was the subsidy for your decision to buy the electric bike?", with responses on a five-point Likert-scale ranging from "Not important at all" to "Crucially important." Figure 3 summarizes the survey responses.

About 64% find the subsidy to be important for their purchase of the e-bike (corresponding to those responding 4 or 5). Only 15% responded that it was not important (those with 1 or 2) and the remaining to be somewhat important (those reporting 3).

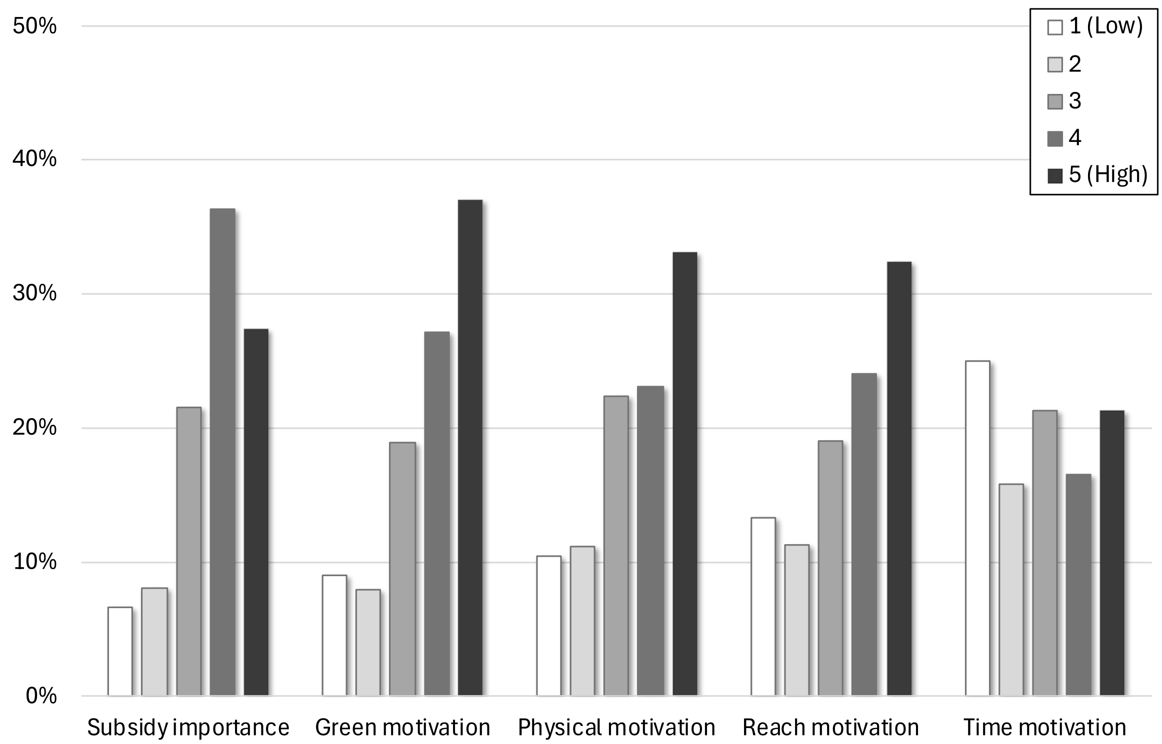
The survey also includes a question what motivated the purchase (also on a five-point Likert scale). The motivations are:

- *Green*: Environmental interest
- *Physical*: More physical activity
- *Reach*: Increase reach
- *Time*: Save time

These motivations broadly maps to the UN climate goals: Climate Action (SDG 13); Health and Well-being (SDG 3); Sustainable Cities (SDG 11); and Responsible Consumption and Production (12).

Figure 3: The Importance of the Subsidy for Purchase and Motivations to Buy an E-bike

This figure displays the frequency of responses to questions about the subsidy and purchase of the e-bike. Possible responses ranges from "Not important at all" (1) to "Very important" (5). Subsidy importance denote the responses to the question "How important was the subsidy for your decision to buy an e-bike?". The questions for motivation are: "What motivated you to buy an e-bike?", followed by "Environmental interest" (Green); "More physical activity" (Physical); "Ability to reach places" (Reach); and "Save time" (Time). There are 2,420 survey responses. The data is obtained from a survey commissioned by the Swedish Environmental Protection Agency.



We find that environmental interest (Green motivation) to be the most important reason for purchasing an e-bike, followed by increasing physical activity and reach. Saving time is the least important motivation.

To investigate how these responses depend on characteristics, we create dummies that take the value of one for responses in category 4 ("Important") and 5 ("Very important") as dependent variables in Probit regressions. The regressions include dummies for car ownership, living in a high populous municipality, having a short commuting distance and living in a municipality with a high public transport density.[7] Public transportation density is defined as the number of bus stations scaled by area of a municipality based on

[7]Statistics Sweden estimates that around one-third of the working population lives within a bike commuting distance of 15 minutes, which warrants this choice.

geographical data from STA. Demographics include age, children and dummies for high disposable income, gender, and university educated.

Table III: Subsidy Importance and Motivation of E-bike Purchase

This table reports marginal effects from probit regressions. In column (1), the dependent variable is a dummy equal to one if the respondent indicated that the subsidy was “Important” or “Very important” (category 4 or 5) in their decision to purchase an e-bike. In column (2), the dependent variable is a dummy equal to one if the respondent indicated that the motivation was “Important” or “Very important” (category 4 or 5) for their purchase decision. Key independent variables include car ownership, residence in municipalities in the top decile of population density (urban), commuting distance of 5 km or less, and residence in municipalities in the top quartile of public transport density. Controls include high income (disposable income > 364,000 SEK), age, gender, university education, and the presence of children in the household. Robust standard errors in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively

	Subsidy	Purchase motivation			
	importance	Green	Physical	Time	Reach
VARIABLES	(1)	(2)	(3)	(4)	(5)
Car owner	0.043*	-0.022	0.049**	-0.090***	-0.070***
	(0.023)	(0.022)	(0.023)	(0.023)	(0.023)
Urban	-0.000	-0.025	-0.045**	0.187***	0.003
	(0.022)	(0.022)	(0.023)	(0.022)	(0.023)
Short commute	0.012	-0.044*	-0.140***	0.056**	0.062***
	(0.023)	(0.023)	(0.024)	(0.024)	(0.024)
High public transport density	-0.000	-0.006	-0.048**	0.070***	0.087***
	(0.021)	(0.021)	(0.022)	(0.022)	(0.022)
High income	-0.046**	-0.036	0.023	-0.051**	-0.044*
	(0.022)	(0.022)	(0.023)	(0.023)	(0.023)
Age	-0.004***	0.001	0.004***	-0.005***	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Women	-0.072***	0.083***	0.089***	-0.003	0.079***
	(0.021)	(0.021)	(0.022)	(0.022)	(0.022)
Children	0.021	0.034	-0.003	0.027	-0.069***
	(0.022)	(0.022)	(0.023)	(0.022)	(0.023)
University	0.034	0.082***	-0.040*	0.049**	-0.018
	(0.022)	(0.022)	(0.023)	(0.022)	(0.023)
Observations	2,430	2,430	2,430	2,430	2,430
Pseudo R2	0.0151	0.0169	0.0321	0.0742	0.0283

Table III presents the regression results. Column (1) reports estimates for the overall, self-assessed importance of the subsidy in the decision to purchase an e-bike. Consistent with the presence of binding budget constraints, younger and lower-income individuals report that the subsidy was more important for their purchase decision. Women report the subsidy to be less important, while car owners report it to be somewhat more important. Potential daily e-bike commuters—defined as individuals living within five kilometers of their workplace—do not find the subsidy to be either more or less important. Likewise, individuals residing in areas with better access to public transportation are no more or less likely to report that the subsidy played a particularly important role.

Turning to specific motivations in columns (2) through (5), car owners appear less motivated by time savings and increased reach, but more motivated by physical activity and cost considerations. This pattern is broadly consistent with an intention to substitute driving with biking primarily for health-related reasons. Given that car owners are, on average, more affluent, the weak but positive association between car ownership and overall subsidy importance may indicate that e-bikes are perceived as relatively expensive even among higher-income households. Women report environmental concerns, time savings, and increased reach as their most important motivations, suggesting that sustainability considerations and convenience play a comparatively larger role for this group.

Individuals living within a reasonable commuting distance to work are less motivated by physical exercise, but more motivated by time savings and increased reach. Those with better access to public transportation exhibit similar patterns, consistent with shorter commuting distances being more common in denser, urban areas.

Overall, the regression results suggest that the subsidy was relatively more important for financially constrained individuals, but less so for those with stronger environmental motivations. Evidence on the targeting of car owners is mixed. On the one hand, car owners appear to respond to the subsidy for financial reasons, potentially complemented by health considerations. On the other hand, individuals living within reasonable commuting distances are less likely to cite physical activity as a primary motivation, instead emphasizing reduced travel time and improved reach. Taken together, a substantial share of subsidy recipients report that the subsidy played an important role in their purchase decision. We interpret this as evidence that a majority of subsidized purchases are additional, consistent with the marked increase in e-bike sales shown in Figure 2.

3.4 Subsidy Take-up and Demographics

Those who obtain the e-bike subsidy are on average older and have higher education and income. Furthermore, the take-up of the subsidy was higher in rural areas. Table IV compares the demographics of our subset with the general population of Sweden, as well as to the subset of recipients who were registered car owners. The share of car owners among subsidy recipients in our sample is very similar to that in the overall population. We then examine the characteristics associated with car ownership within this group. Subsidy recipients are less likely to own a car if they live in urban areas, have short commutes, or good access to public transport. Car ownership is higher among older, higher-income individuals and households with children, while women and university-educated recipients are substantially less likely to own a car (see Table A.3 in appendix).

Table IV: Demographics of Subsidy Recipients and Car Owners

This table reports demographic characteristics of Swedish citizens, all subsidy recipients (N=89,621), and the sub-sample car owning subsidy recipients (N=52,840). Individuals are classified into quartiles of age and income. University is defined as having completed at least post-secondary education less than 3 years. Income denoted in Swedish Krona. Commuting distance is the Euclidean distance between home and work coordinates, where short distance is five kilometers or less. Urban areas are the 30 most populous municipalities in Sweden. Public transport density represents the density of bus stations in municipalities, where high indicates the upper quartile of highest public transport dense municipalities in Sweden. Data on Swedish population is retrieved from Statistics Sweden for the year 2018 on individuals of the age of 18 and older.

	Swedish population	Subsidy recipients	Car owners
Gender			
Men	0.50	0.52	0.64
Women	0.50	0.48	0.36
Age			
18-34	0.27	0.14	0.08
35-49	0.23	0.26	0.24
50-64	0.22	0.35	0.39
65+	0.24	0.25	0.29
Income			
0-171	0.25	0.14	0.10
171-273	0.25	0.27	0.24
273-364	0.25	0.27	0.29
364+	0.25	0.32	0.37
University			
Yes	0.38	0.49	0.46
No	0.62	0.51	0.54
Mobility & transport			
Car owner			
Yes	0.60	0.59	1.00
No	0.40	0.41	0.00
Urban			
Yes	0.41	0.33	0.27
No	0.59	0.67	0.73
Commuting distance			
Short	n/a	0.54	0.54
Long	n/a	0.46	0.46
Public transport density			
Low	0.54	0.50	0.55
High	0.46	0.50	0.45

Our result highlights that a considerable fraction of subsidy recipients did not own a car, implying perhaps a limited scope for transport substitution. It is to this issue of behavioral substitution that we now turn.

4 Behavioral Substitution

We continue our analysis by addressing whether the ownership of e-bikes carries over to changes in car driving behavior, i.e., whether e-bikes dis-incentivize car driving. In this section we present estimates of VKT reductions based on car registry data for the time before and after the purchase of an e-bike. We do so in a couple of ways, allowing for different assumptions with respect to the car data that we obtain from the STA. Then, as we have both survey data and car registry data, we can make direct comparisons between the two in order to identify similarities and differences in self-reported and recorded driving behavior.

4.1 Driving Behavior

Because the subsidy was implemented in 2018 and only marginally affected 2017 sales (Figure 2), we split the sample into pre- and post-subsidy periods. Vehicle Kilometres Travelled (VKT) are obtained from registry inspection data and provide a reliable measure of driving distance.[8]

Table V summarizes registry data for subsidy recipients from 2016 to 2019. Panel A shows that car ownership is stable at around 60% throughout the period. We find no evidence that obtaining an e-bike affected the extensive margin of car ownership: the number of individuals buying or selling cars is small and constant over time (Appendix Table A.2). In total, 52,840 individuals own at least one car both before and after the subsidy period.

Two measurement issues arise when using registry mileage data. First, mileage is estimated rather than observed during the first three years after purchase of a new car. Second, registry mileage does not account for within-year changes in ownership, which may distort annual mileage in the first or last year of ownership. To address these concerns, we analyze three increasingly restrictive samples of individuals observed both before and after the subsidy: (i) all car owners ("All", 52,840), (ii) owners excluding years in which a car is first acquired ("Ownership", 45,990), and (iii) owners of cars older than three years ("Age", 31,219).

[8]New cars are inspected only after 36 months. For these, the STA provides mileage estimates. We report results under alternative measurement assumptions.

Table V: Registry Car Data: Ownership and VKT

This table reports car ownership and use from registry data across the years 2016 to 2019 around the subsidy intervention. Panel A reports the number of individuals who own a car (*I. All*) in the sample. The last column reports car owners in both the pre- and post subsidy period who owned a car in at least one year pre-subsidy (2016 or 2017) and at least one year post-subsidy (2018 or 2019). The rows labeled *II. Ownership* partitions car owners into groups based on the continuity of car ownership, where continuous owners are those who owned cars the year before and after the period of interest. The partition labeled *III. Age* partitions ownership on age of the car (larger than three). Car fleet partitions cars on HEVs (Hybrid Electric Vehicles, including fully electric cars) and ICEV's (Internal Combustion Enginge Vehicles, gasoline or diesel powered cars). Panel B reports the average car use. VKT (Vehicle Kilometres Travelled) is reported both in absolute terms as well as relative to municipality averages. Pre- and post difference is calculated by averaging VKT for the two years after and before the subsidy period.

Panel A: Car ownership (full sample)

		Pre-subsidy		*Post-subsidy*		*In pre- & post*
		2016	*2017*	*2018*	*2019*	*sample*
Individuals	All	89,621	89,621	89,621	89,621	89,621
I. All	Non-car owners	35,644	35,241	35,303	35,159	36,781
	Car owners	53,977	54,380	54,381	54,462	52,840
II. Ownership	*Discrepant car owners*		4,875	5,091	4,459	6,850
	Continuous car owners		49,505	49,740	50,003	45,990
III. Age	*New car owners*	10,236	10,916	10,738	9,768	21,261
	Older car owners	43,741	43,464	43,580	44,694	31,219
Car fleet	Total no. of vehicles	76,476	77,513	77,489	77,351	
Type	HEV's	4,956	5,288	5,645	6,089	
	ICEV's	71,520	72,201	71,868	71,263	
Age	$\leq$ 3 years	16,850	18,361	18,610	17,763	
	$>$ 3 years	59,626	59,128	58,903	59,589	

Panel B: Individual VKT (car owners)

		Pre-subsidy		*Post-subsidy*		*Pre-post*
		2016	*2017*	*2018*	*2019*	*Diff.*
I. All	VKT (abs.)	15,660.68	15,422.33	15,258.99	14,652.12	-616.10
	VKT (rel.)	726.42	641.55	614.09	436.10	-204.87
II. Ownership	VKT (abs.)		15,765.55	15,578.62	14,946.66	-681.69
	VKT (rel.)		659.21	639.58	458.11	-260.99
III. Age	VKT (abs.)	16,330.34	16,031.22	15,764.45	15,182.36	-1,040.37
	VKT (rel.)	847.30	711.93	617.08	529.00	-589.60

Panel B of Table V reports yearly VKT for the two years before and after the subsidy. Average driving is around 15,000 kilometers per year and declines gradually over time. Using home and work coordinates, we estimate annual commuting distance at approximately 5,200 kilometers—about one-third of total driving—consistent with evidence from other European countries.[9]

For all car owners, we compute the pre–post change in driving as the difference between average VKT in the two years before the subsidy (2016–2017) and the two years

[9] Eurostat mobility statistics show that 27% of daily travel distance in Germany is work-related, with higher shares in more sparsely populated countries.

after (2018–2019). This difference is 616 kilometers (3–4%) in absolute terms. Because aggregate driving trends may confound this comparison, we also measure VKT relative to municipality averages; in relative terms, the estimated reduction is smaller, about 205 kilometers. Appendix Figure A.2 shows substantial heterogeneity, with many individuals increasing rather than decreasing driving.

When focusing on older vehicles, estimated reductions become larger: about 1,040 kilometers in absolute terms and 590 kilometers relative to municipality averages. These larger effects likely reflect both improved measurement quality and differences in driving behavior among owners of older cars.

Overall, registry data indicate annual reductions in driving between 610 and 1,040 kilometers depending on sample restrictions, corresponding to 3–6% declines. When adjusting for municipality-level trends, estimated reductions fall to 205–590 kilometers. These figures should be interpreted as upper bounds on behavioral substitution attributable to e-bike use.

4.2 Heterogeneity in Driving Behavior

Driving responses to the subsidy display substantial heterogeneity (see Appendix Figure A.2). Table VI reports estimates across subsamples defined by urban residence, commuting distance, public transport density, and income.

Panel A compares relative vehicle kilometers traveled (VKT) for urban and rural residents. Urban residents drive significantly less than rural residents and reduce driving by roughly twice as much after the subsidy—about 161 kilometers per year more.

Panel B splits the sample by the Euclidean home–work distance, defining a short commute as five kilometers or less. More than half of the sample falls into this category. Individuals with longer commutes drive on average 1,222 kilometers more per year than those with shorter commutes. The difference in driving reductions is negative, indicating that individuals with longer commutes reduce driving less, although the estimate is not statistically significant.

Panel C of Table VI shows that, on average, subsidy recipients with good access to public transport drive less than those with poorer access. However, the difference in the reduction in driving between these groups is close to zero. Panel D of Table VI shows that, on average, high-income subsidy recipients drive more than lower-income recipients, with an annual difference of 1,048 km. However, the difference in the reduction in driving between these groups is again close to zero.

Overall, the combined results from Table IV and Table VI indicate substantial heterogeneity in adoption of e-bikes and subsequent changes in driving behavior. A higher propensity for subsidy take-up does not necessarily correspond to greater behavioral

Table VI: Substitution Heterogeneity

This table reports averages of relative VKT (measured relative to municipality averages) across several subsamples. Panel A splits the sample into urban and rural residents, where the urban areas are the 30 most populous municipalities in Sweden. The urban (rural) sample consists of 14,122 (38,718) individuals. Panel B splits the sample by commuting distance, where the Euclidean distance between home and work coordinates is five kilometers or less. The short (long) distance subsample consists of 9,414 (7,935) individuals. Panel C splits the sample on public transport density, where upper quartile of highest public transport dense municipalities in Sweden. The high public transport density has 23,793 individuals and the low sample has 29,047. Panel D splits the sample on disposable income where high income is above 364,000 Swedish Krona. The high (low) income sample consist of 19,304 (33,536) individuals.

Panel A: Rural vs. Urban			
VKT (rel)	*Rural*	*Urban*	*Diff.*
Pre-average	877.06	231.48	645.57 ***
Pre-post diff.	-161.87	-322.74	160.88***

Panel B: Commuting distance			
VKT (rel.)	*Short*	*Long*	*Diff.*
Pre-average	109.63	1,222.19	1,112.56 ***
Pre-post diff.	-218.66	-141.57	-77.10

Panel C: Public transport density			
VKT (rel)	*Low*	*High*	*Diff.*
Pre-average	1,006.29	336.12	-670.17 ***
Pre-post diff.	-204.61	-205.18	0.57

Panel D: Income			
VKT (rel)	*Low*	*High*	*Diff.*
Pre-average	321.67	1,369.62	1,047.95 ***
Pre-post diff.	-198.86	-215.30	16.44

change.

For instance, rural residents display high take-up of the green technology but limited substitution away from “brown” travel, whereas urban residents, despite lower take-up, exhibit greater behavioral change. Similarly, individuals with longer commutes and those with poor access to public transport owned cars at higher rates and drove more prior to the subsidy, suggesting substantial scope for substitution. Yet, in practice, these groups did not reduce their driving more than individuals with shorter commutes or better public transport access.

Relatedly, higher-income individuals were more likely to claim the subsidy, more likely to own a car, and had higher pre-subsidy driving levels. Nevertheless, they did not reduce their driving more than lower-income recipients. The subsidy thus disproportionately benefited higher-income households without generating proportionally greater substitution. High potential for substitution therefore does not automatically translate into realized behavioral change.

4.3 Registry versus Survey Data

In this section, we turn to survey evidence to assess driving reductions based on self-reported travel distances. Table VII presents a cross-validation between self-reported survey- and registry estimates.

Table VII: Registry versus Survey Data

This table reports survey car use and registry ownership across the pre- and post-subsidy intervention. The sample is based on 1,944 individuals who reported to use their e-bike in their daily commute. Panel A reports transition matrices of the number of individuals in the survey sample who claim they use a car before and after the subsidy (*All car users*), and among those, the number of individuals who own a car (*Car owners*). Panel B reports the average car use. Days of use is the number of days per year on which an individual reports to use a car for commuting, extrapolated from weekly use. Reported VKT is calculated by multiplying days of use with self-reported commuting distance. Panel C reports the mean difference in commuting distance as well as register VKT pre- and post subsidy for Car owners. Reported VKT is calculated for the full survey sample using self-reported VKT. Register VKT shows the driving reductions from the subset of car owners in the survey using registry data.

Panel A: Car use and ownership (survey sample)

Respondents	1,944	Non-car users	633				
		Car users	1,311	Non-car owners	293		
				Car owners	1,018	Substitute some	751
						Substitute all	267

Panel B: Cross-validation survey-registry

		Pre-subsidy	*Post-subsidy*	*Pre-post diff.*
Car users	Days of use	170.70	77.25	-93.44
	Reported VKT	3,243.78	1,577.29	-1,659.19
Car owners	Reported VKT	3,419.78	1,674.21	-1,736.17
	Registry VKT	15,142.73	14,442.42	-700.30
	Rep-reg diff.			-1,035.87***

Panel C: Pre-post difference (car owners)

Reported substitution		*Some*	*All*	*Some-all diff.*
Pre-post diff.	Reported VKT	-1,530.15	-2,315.66	785.51***
	Registry VKT	-400.66	-1,543.13	700.30**
	Rep-reg diff.	-1,129.49***	-772.53	

We refer to those in the survey who reported having used a car for commuting as *car users*, and those who appear in our registry data as *car owners*. Panel A of Table VII reports the sample of survey respondents who record their commuting behavior pre- and post purchase. Of these 1,944 individuals, two-thirds (67%) claimed having used a car for the majority of their commute before they bought an e-bike. Matching the survey with registry data shows that 84% of car users own cars. We use this intersection of car-owning survey respondents to cross-validate our registry estimates.

Panel B of Table VII shows the VKT estimates based on both survey and registry data.

First, we focus on individuals who reported using a car as their main transportation mode in their commute before purchasing an e-bike. On average, these car users reported commuting with a car for 171 days per year resulting in a total VKT of 3,200 kilometers. After having purchased an e-bike, the same individuals reported commuting with their car for only 77 days per year on average, resulting in a decrease of 93 days. Using the reported change in driving days and self-reported commuting distance, we calculate the reduction in driving to be around 1,600 kilometers (half of their car use). The estimated average reduction for the smaller subsample of car owners is similar at around 1,700 kilometers. When comparing the reported estimates with registry estimates, we find that the survey-based reductions are much higher. The survey based estimate is around 1,000 kilometers higher than those obtained using registry data. Note that our adopted extrapolation strategy closely aligns with the existing survey-based e-bike literature.

The difference between reported and registered distance may be due to the way reported commuting days are extrapolated into yearly reductions. We can compare the number of reported commuting days to what is reported for Swedish drivers in general. Trafikanalys (2020) estimate the average commuting days as a function of distance to work. We find the self-reported number of commuting days to be almost identical. Therefore, the extrapolation from commuting days seems reasonable, even if the methodology is somewhat generalized.

Finally, Panel C of Table VII examines the gap between self-reported data and registry data. A subset of respondents (257 individuals or 24%) reported that they stopped driving entirely after purchasing an e-bike, fully replacing their car commutes with biking. We compared the distance reductions for this group to the rest of the sample, who only partially replaced their driving. The results show that the discrepancy between survey and registry data is statistically significant and larger for those who reported only reducing their driving, compared to those who claimed to have completely stopped driving. Additionally, individuals who fully replaced driving with biking reduced their VKT by approximately 700 to 786 kilometers more per year than those who only partially substituted driving. This difference in reductions is consistent across both the self-reported and registry data. Thus, while survey estimates may overstate reductions on a broader scale, they accurately reflect the similar magnitude of reductions between those who fully substitute driving and those who do not.

In conclusion, we find that reductions in VKT based on self-reported surveys tend to be significantly higher than those reflected in registry data. Several factors could explain this discrepancy. First, while our method of converting weekly trips and distances provides reasonable estimates overall, it involves extrapolations that may introduce errors. Second, although respondents may accurately report changes in their driving habits, these changes might be short-term and not reflective of the longer periods captured by registry data, suggesting a decline in substitution over time. Additionally, car owners may offset reductions in some trips by increasing driving for other purposes. Third, individuals may overestimate the extent to which they substitute driving with e-bike use. Notably, the gap between reported and registered VKT reductions is much larger among those who report partial substitution from driving compared to those who completely stop using their car. Our results therefore speak to a mechanism in which people overestimate how much they are able to reduce driving.

5 Implications for Health, Traffic Congestion, and Carbon Emissions

This section discusses the potential benefits of e-biking and substitution away from car use. While the primary objective of the Swedish e-bike subsidy was to reduce driving and associated emissions, shifts from car travel to e-biking may generate a broader set of co-benefits. These include improvements in physical health through increased travel-related physical activity, reductions in traffic congestion and travel delays, lower local air pollution and noise, and potential welfare gains from reduced fuel expenditures and parking demand.

The magnitude of these benefits depends critically on the extent to which e-bikes substitute for car trips rather than other modes of transport, as well as on local commuting patterns and infrastructure. In the following subsections, we assess the empirical relevance of these channels in turn. We emphasize that while some benefits—such as health improvements or congestion relief—may materialize only gradually or in specific settings, understanding their potential scope is important for evaluating the overall effectiveness of e-bike subsidies.

5.1 Health Effects

Given the modest reductions in car travel that we document, the implied increases in physical activity—and thus near-term health benefits—are likely to be limited.

The World Health Organization (WHO) recommends at least 150 minutes per week of moderate-intensity physical activity, or 75 minutes per week of vigorous activity, or an equivalent combination.[10] At 20 km/h, these thresholds correspond to roughly 25–50 kilometers of e-biking per week (about 1,300–2,600 kilometers per year), depending on whether e-biking is closer to vigorous or moderate intensity. This back-of-the-envelope

[10]See WHO physical activity recommendations. We assume an average e-biking speed of 20 km/h.

calculation suggests that, for many individuals, meeting WHO-recommended activity levels would require replacing a substantial share of regular commuting with e-biking.

Moreover, potential health benefits from increased physical activity are likely to accrue over longer horizons and are therefore not directly observable in our setting. In the absence of individual-level health outcomes, we cannot assess short-run health effects associated with switching from car travel to e-biking. Importantly, increased exposure to traffic while cycling may also raise accident risk, implying that the net short-run health effect of substitution from car travel to e-biking is theoretically ambiguous.

5.2 Traffic Congestion

We next show that e-bike take-up was not systematically higher in areas where traffic congestion is likely to be more salient. To do so, we estimate cross-sectional regressions of subsidy adoption across Sweden's 290 municipalities. The dependent variable, $Adoption_i$, is the number of e-bike subsidy payouts per inhabitant. The main explanatory variables are population density (measured as thousands of inhabitants per square kilometer) and car ownership per capita. We additionally control for average age, median income, and the share of university-educated residents, and include county fixed effects for Sweden's 21 counties.[11]

$$Adoption_i = \alpha + \beta_1 Population_i + \beta_2 Cars_i + \beta_j X_{j,i} + \delta_c + \epsilon_i. \tag{2}$$

Table VIII reports the results. Column (1) shows that e-bike take-up is negatively associated with population density, indicating that adoption was not disproportionately concentrated in the most urbanized municipalities, where congestion pressures are typically highest. Columns (2) and (3) further show that adoption is negatively related to car ownership per capita, even after controlling for population density. A one–standard deviation increase in car ownership, combined with the coefficient in Column (3), is associated with a decline of 0.59 e-bike subsidies per thousand inhabitants, corresponding to a 7% decrease relative to the mean adoption rate of 7.91.

Column (4) decomposes car ownership into internal combustion engine vehicles (ICEVs) and hybrid electric vehicles (HEVs). E-bike take-up is lower in municipalities with higher ICEV prevalence, but higher in municipalities with greater HEV penetration. This pattern suggests that adoption was more common in areas where households had already begun transitioning toward more fuel-efficient or lower-emission transport modes, rather than in areas facing the most severe congestion constraints. Consistent with this interpretation, the Appendix shows that e-bike take-up is also positively associated with electoral support for the Green Party.

[11] All municipal-level data are obtained from Statistics Sweden and described in the Appendix.

Table VIII: E-Bike Take-up

This table presents regression results where the dependent variable is the number of e-bike subsidies per thousand inhabitants across Sweden's 290 municipalities. Independent variables include car ownership per capita (measured as the number of cars per thousand inhabitants), population density (thousands of inhabitants per square kilometer), and a set of demographic controls. In Column (4), car ownership is decomposed into internal combustion engine vehicles (ICEVs) and hybrid electric vehicles (HEVs). Controls include the population shares of women, young adults, individuals with higher education, and median log income. County fixed effects are included for Sweden's 21 counties. Robust standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	E-bike Adoption			
VARIABLES	(1)	(2)	(3)	(4)
ICEVs				-0.016***
				(0.004)
HEVs				0.141***
				(0.040)
All Cars		-0.007*	-0.009**	
		(0.004)	(0.004)	
Population Density	-0.585**		-0.732***	-1.067***
	(0.233)		(0.218)	(0.291)
County FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	290	290	290	290
R-squared	0.689	0.688	0.693	0.707

Taken together, these municipal-level patterns indicate that the subsidy was not primarily taken up in locations where congestion relief would plausibly have been greatest. Instead, adoption was relatively higher in municipalities with fewer cars per capita and greater prevalence of hybrid vehicles. This geographic distribution is consistent with the limited behavioral response observed in the odometer data: if adoption is concentrated in areas with weaker congestion pressures and among populations with stronger pro-environmental preferences, the scope for large reductions in driving—and hence congestion—is inherently limited. Overall, the spatial heterogeneity in take-up reinforces the interpretation that the subsidy's direct impact on traffic congestion was modest.

5.3 *Reduction of Carbon Dioxide Emissions*

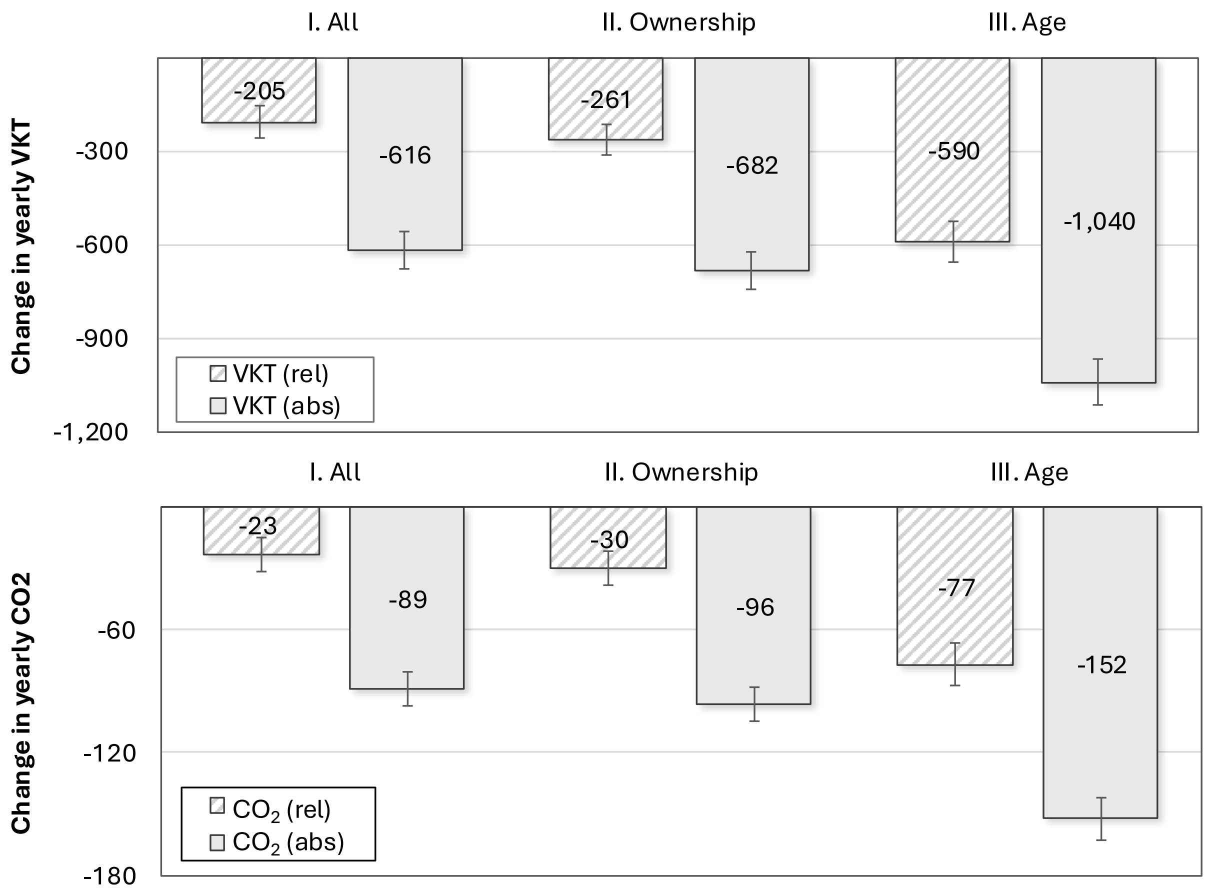
Figure 4 plots the mean average reductions of VKT translated into units of carbon dioxide for our estimates in the previous sections. The detailed car registry data allows us to adjust for emissions individually with respect to type of car driven.[12] The VKT reduction of all car owners present in the pre- and post period is 616 kilometres in absolute, and

[12]Car-type emissions are taken from Gottleben et al (2021).

205 kilometers, in relative terms. This translates to an annual reduction of 89 kilograms of CO_2 emissions overall, and 23 kilograms in relative terms. Clearly, the main effect on emissions comes from a reduction of distance travelled but there is also a smaller effect on reductions coming from the composition of the car fleet. The implied emission per kilometer is 0.140 kilograms when considering the full sample which rises to 0.146 when considering only older cars (obtained by dividing emissions with VKT).[13]

Figure 4: Estimates of VKT and CO_2 emissions

This figure displays the different estimates of the change in VKT and CO_2 emissions before and after the subsidy. The VKT driving reductions in the upper panel are taken from Table V. The associated CO_2 emissions in the lower panel are measured in kilograms and calculated at the car level by multiplying yearly VKT (relative or absolute) by the emission intensity of the car type.



In summary, we find CO_2 reduction estimates in the range of 89 to 152 kilograms per year in absolute terms in the registry data in the time period surrounding the subsidy. The absolute measure captures total driving reductions that may not only be attributed to the e-bike and possibly excludes changed driving behavior from people using but not owning a car. The relative, municipality adjusted, reductions are much lower ranging

[13] Fyhri, Sundfør, and Weber (2016), who log individual travel distances in Norway, estimate carbon reduction in the range of 137 to 155 grams per kilometer.

from 23 to 77 kilograms per year. This tells us that overall reductions in absolute terns likely include a more general reduction outside the scope of the subsidy intervention.

6 Program Cost and Benetifts

We calculate lifetime emission reductions relative to the overall program cost to infer the efficacy of the subsidy. We do so by using our measured reductions as well as under the assumption of complete substitution. For this analysis, we focus on the benefits obtained from reducing car use and the saving in carbon emissions as a result. We do not consider potential emissions savings from public transportation since this is considered second order compared to car use.[14] We focus on consumers only. Our estimate of a complete pass-through means that the effect on the producer surplus is minimal, and we can focus on how a dollar of subsidy changed consumer behavior in terms of reduction in car kilometer usage. Details of this aggregation is found in Appendix A.3

6.1 Estimated Lifetime Carbon Savings and the Shadow Cost of Carbon

Figure 5 plots net aggregate emissions, defined as emissions savings from vehicle substitution (green bars) minus emissions from e-bike manufacturing and charging (grey bars). To calculate the aggregate emissions savings, we multiply estimated change in car CO_2 emissions with the number of car owners (see Figure 4). Aggregate manufacturing emissions are equal to 130 kilograms of carbon emissions times the number of subsidy recipients. We calculate aggregate e-bike use emissions as the product-sum of average change in VKT, subsidy recipients, and the estimated emissions per kilometer. We sort our results based on the estimated carbon savings which is lowest in our general car registry sample for relative VKT, and highest for the absolute VKT based on older cars. For our narrowest estimate of emission savings, the net savings of the e-bike subsidy are negative. The consequent estimates provide net positive life-time reductions that range from 750 to over 50.000 tons of CO_2 saved.

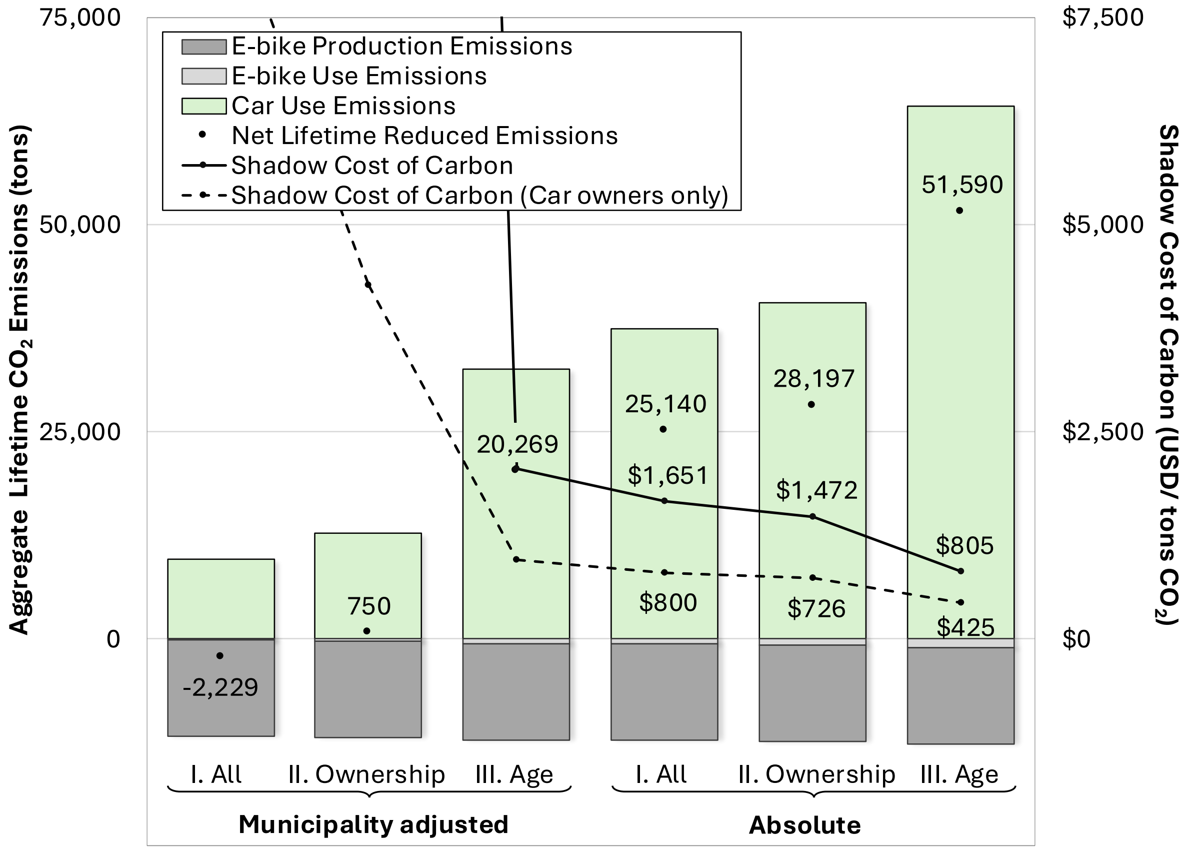
Figure 5 also plots the Shadow Cost of Carbon (SCC) to relate the cost of the subsidy program to the benefits from reduced emissions. Specifically, we divide total program costs by net aggregate emissions savings, yielding an estimated dollar cost per ton of carbon emissions consistent with the subsidy policy breaking even.

We do so in two ways. First for the full sample, acknowledging that around 40% of recipients did not own a car in the first place which imposes a cost with no associated

[14]The SEPA reports that the 2018 total carbon emissions from all means of transportation in Sweden was 17 million tons in total of which cars were responsible for 10 million tons—twice to the amount of trucks (https://www.naturvardsverket.se/data-och-statistik/klimat/vaxthusgaser-utslapp-fran-inrikes-transporter/ accessed on December 9, 2021).

Figure 5: Lifetime Impact of E-bikes and Shadow Cost of Carbon

This figure displays the estimations of lifetime CO_2 impact of e-bikes and the implied shadow cost of carbon that equates benefits to costs. Lifetime emissions are calculated as the 8-year sum of yearly emissions (green bar for reduction in car emissions, dark grey bar for increase in emissions due to e-bike use) in addition to the production emissions for e-bikes (light grey bar). Bold number at the top of the bars show the net lifetime aggregate emission reduction for the corresponding estimate. The shadow cost of carbon is calculated as the aggregate net lifetime impact of an e-bike divided by the total cost of the program. The shadow cost of carbon for car owners only is obtained by performing the same calculation but using the subsidy cost for car owners only.



benefit of carbon reduction. Second, by restricting our sample to car owners only. We aggregate the cost as well as carbon reductions over these 60% of individuals. The results of these calculations are indicated by lines in Figure 5 but only traced out for the aggregate reduction categories where there are meaningful reductions in the three bars to the right.

The solid line in Figure 5 shows that the shadow price of carbon needs to be close to $1,651 per ton in order to motivate the cost of the subsidy based on all driving. If it would have been possible to target car owners only, this number drops to $800 but is still high. The absolute, older car owner reductions are the most favorable estimates of carbon emission savings which translate to a shadow price of carbon of around $805 per ton ($425 for all car owners only) which is still inconsistent with most conventional estimates of carbon pricing. Conventional estimates of the SCC used in policy evaluation are typically in the range of $50–$100 per ton of CO_2. Although recent integrated assessment model revisions yield higher values under alternative assumptions about discounting, climate risk, and damages (Rennert et al (2022) and Gillingham and Stock (2018)), these estimates generally remain in the low hundreds of dollars per ton and thus well below the implied shadow prices required to justify the subsidy in our setting.

6.2 Counterfactual: A Commuter-Targeted Subsidy

The Swedish subsidy was tied exclusively to the purchase of an e-bike and did not condition eligibility on car ownership or subsequent use. As a counterfactual exercise, we therefore re-estimate the implied benefits under the assumption of a commuter-targeted subsidy that induces full substitution from car commuting to e-biking.

Our estimates indicate average annual commuting distances of approximately 5,200 kilometers among subsidy recipients. A complete replacement of car commuting with e-biking would therefore imply a reduction in carbon emissions of roughly 748 kilograms per person per year. Under this counterfactual, the subsidy would break even in terms of climate benefits at an implied social cost of carbon of approximately $139 per ton if applied to all subsidy recipients. If instead the policy were perfectly targeted to car owners, the corresponding break-even social cost of carbon would fall to about $79 per ton.

In other words, the fiscal cost of the subsidy would be aligned with the value of avoided emissions only under a scenario involving near-complete substitution away from car commuting. Such a scenario would also plausibly generate substantial health benefits, as discussed in Section 5.1. While this counterfactual is intentionally extreme, it provides a useful benchmark for assessing the extent to which the observed behavioral responses fall short of the levels required for the subsidy to be cost-effective on climate grounds alone.

6.3 Comparing to Survey Estimates in the Literature

Table IX provides a non-exhaustive overview of studies estimating carbon savings from e-biking and highlights the wide variation in reported effects.[15] These comparisons suggest that our findings are not driven by idiosyncrasies of the Swedish context or our particular sample of subsidy recipients. Rather, the discrepancy arises because measured changes in driving behavior are substantially smaller than what survey-based substitution rates would imply.

Most existing studies rely on relatively small survey samples—often only a few hundred respondents—to estimate car-to-bike substitution. These survey-based studies report annual carbon savings that range widely, from 87 to 744 kg CO_2 per person (column "Survey"). A smaller set of studies combine self-reported surveys with measured mobility data such as GPS traces or odometer readings (column "Measured"). A third group relies on hypothetical full-substitution scenarios, typically assuming that all commuting is replaced by e-biking, producing estimates in the range of 580–750 kg CO_2 per person per year (column "Hypothetical"). Unsurprisingly, the hypothetical estimates are consistently larger because they assume the highest feasible level of substitution.

We benchmark our estimates against these three groups. First, using car odometer readings for the full sample of subsidy recipients—adjusted for regional trends in driving—we estimate carbon savings between 23 and 77 kg CO_2 per person per year. These values are substantially lower than those reported in most survey-based studies. Second, using the SEPA survey to calculate carbon savings yields an estimate of 243 kg CO_2 per person per year, squarely within the range of survey-based results reported in Table IX. Finally, assuming that e-biking fully replaces all commuting in our sample produces an estimated reduction of 750 kg CO_2 per person per year, closely mirroring the hypothetical full-substitution estimates for commuting in the literature.

[15] While we focus on papers that calculate carbon savings, a broader literature examines modal substitution resulting from e-biking, including Bucher et al. (2019), Söderberg, Adell, and Hiselius (2020), Sun et al. (2020), de Kruijf et al. (2018), Fyhri and Sundfør (2020), and Ling et al. (2015).

Table IX: E-bike Use and Estimated Reductions of Carbon Emissions

This table summarizes studies of carbon reductions attributable to e-bike use. Studies are grouped by the type of data used to estimate modal substitution: measured data (e.g., GPS or odometer), self-reported survey data, or hypothetical full-substitution models. We report key study characteristics, substitution estimates, and sample details. All substitution estimates are normalized to annual reductions, using either 12 months (*) or 48 weeks (**) of assumed yearly use.

	Scope		**Estimates**			CO_2 Reduction
Paper	Country / Year	Sample	Measured	Survey	Hypothetical	(kg/person/year)
This study	Sweden (2016–2019)	52,840 (89,621)	✓			23–77
	Sweden (2018)	1,028		✓		243
	Sweden (2018)	27,628			✓	750
Fyhri, Sundfør & Weber (2016)	Norway (2015)	153	✓			144
	Norway (2015)	377		✓		87
Johnson, Fitch-Polse & Handy (2023)	US (2020–2022)	75	✓			528*
	US (2020–2022)	577		✓		144*
McQueen, MacArthur & Cherry (2020)	US (2013)	1,796		✓		225
Hiselius & Svensson (2017)	Sweden (2013)	321		✓		349
Hagedorn, Meier & Wessel (2025)	Germany (2016–2022)	181		✓		481
Bigazzi, Hassanpour & Bardutz (2025)	Canada (2021)	153		✓		744**
Pierce, Nash & Clouter (2013)	England	n/a			✓	748
Philips, Abable & Chatterton (2022)	England	n/a			✓	580–750

7 Conclusion

Increased concern over global warming has led governments to introduce financial incentives aimed at accelerating the adoption of green household technologies. Yet many such programs have proved less effective than anticipated.[16] As emphasized by Aghion et al. (2023), climate policy is shaped by political and preference-driven forces, and its

[16]See, for example, Murray et al (2014), Cullen (2013), and Davis, Fuchs, and Gertler (2014).

effectiveness depends not only on technological availability but also on households' behavioral responses and willingness to adopt cleaner alternatives.

Using administrative data on all recipients of a nationwide e-bike subsidy in Sweden, matched to rich demographic and vehicle-use information, we assess both the effectiveness of the subsidy and the conditions under which it might generate meaningful sustainability benefits. On the targeting side, we find almost complete pass-through to consumers and additionality of roughly two-thirds, indicating that the subsidy successfully induced a substantial number of new purchases. Recipients tend to be older and higher-income. However, they are no more likely to own a car and tend to live in municipalities where green mobility is already common, which limits the potential for the subsidy to displace "brown" behaviors.

On the behavioral side, registry-based odometer data reveal only modest reductions in driving—on the order of 23–77 kg CO_2 per person per year—with substantial heterogeneity across individuals. Self-reported reductions imply larger, but still moderate, savings of around 243 kg CO_2 per person, while a hypothetical scenario in which all car commuting is fully replaced by e-biking yields potential savings of roughly 748 kg CO_2 per person. These comparisons suggest that low realized substitution, rather than data limitations or measurement error, is the principal bottleneck.

A simple cost–benefit calculation illustrates the implications: given observed behavior, the implied carbon price required for the subsidy to break even is approximately $800 per ton. Only under the extreme counterfactual in which all commuting by car is replaced with e-biking does the implied carbon price fall to levels that approach standard estimates of the social cost of carbon (Nordhaus (2017)). This illustrates how strongly the welfare evaluation hinges on behavioral substitution rather than adoption alone.

Overall, our results highlight the central challenge of using broad technology subsidies to achieve sustainability goals. Although the policy stimulated significant e-bike adoption and was valued by recipients, it produced only modest reductions in driving, emissions, congestion, and physical inactivity. The effectiveness of such subsidies hinges not on adoption per se, but on verifiable behavioral change that displaces carbon-intensive modes of transport. Without stronger behavioral responses, broad-based green-technology subsidies risk delivering symbolic progress rather than substantive environmental benefits.

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Appendix

This appendix presents complementary results to the analysis in the main paper. Section A.1 presents details of the matching procedure between the subsidy data obtained from Statistics Sweden and the bike insurance data obtained from Solid. Section A.2 presents details of the car registry data obtained from the Swedish Traffic Authority, which Statistics Sweden has matched to our subsidy data. Section A.3 presents the assumptions and calculations for the life-time emissions savings and costs associated with substitution away from driving. Section A.4 provides a summary of the regional data and how take-up relates to voting outcomes in the Swedish 2018 elections.

A.1 Insurance Data

The original data from Solid includes almost 700,000 observations of bikes insured from January 2017 to October 2019 of which we can identify a subset of 91,506 e-bikes. Table A.1 presents a detailed description of the matching process.

Among the insured 91,506 e-bikes, there are 47,382 transactions during the subsidy period of October 2017 to October 2018 (or 3,613 e-bikes per month), compared to 17,896 transactions before the subsidy period from January to September 2017 (or 2,084 e-bikes per month) and 26,228 transactions after the subsidy period from November 2018 to October 2019 (or 2,135 e-bikes per month). That is, monthly transactions during the subsidy period are around 1.7 times higher than those outside the subsidy period.

Table A.1: E-bike Sales and Subsidies

This table reports the number of e-bikes in the Solid insurance sample and the coverage in the subsidy data from the Swedish EPA (SEPA). The original sample consists of 695,587 insured bikes of which 91,506 are identified as e-bikes. The columns presents the number of insured e-bikes by time period: before the subsidy (9 months from January 2017 to September 2017); during the subsidy (13 months from October 2017 to October 2018), and after the subsidy (10 months November 2018 to October 2019). The two data sets are matched by considering purchases from the same retailer and insurance policies that correspond to subsidy data on zip-code, retailer, birth-year and brand. We use a subsample for the regressions to ensure that e-bike models are sold in all the three sub-periods and that they are distributed among a sufficient number of retailers. The regression sample contains the most popular 38 models sold by 49 retailers with of 20,586 observations that overlap. The final row shows that 7,914 out of 10,576 e-bikes were sold with a subsidy in the Solid sample during the period it was in effect.

	Solid				**SEPA**
Sample (No. of months)	All (34)	Before (9)	During (13)	After (10)	During (13)
All bikes	695,587				
All e-bikes	91,506	17,896	47,382	26,228	29,794
Top models	37,155	7,233	19,495	10,427	14,655
Top retailers	20,586	3,788	10,576	6,222	7,914

Since price and model are sometimes missing in the Solid data set we match the SEPA subsidy to Solid by dealer, brand, gender, year of birth and month of purchase. During the full subsidy period, we are able to match 29,794 transactions to subsidy information, or roughly 63% of the transactions. In other words, around 37% of the e-bikes sold during the subsidy period did not receive a subsidy. There are two main reasons for this. One is that customers who bought the bike did not submit or properly fill out the paper work required to receive the subsidy. Customers had to send a form to SEPA including the receipt of purchase. The second is data entry error either on the part of Solid or SEPA that prevent a match.

To address the latter data entry issue, we apply a series of screens to our sample. First, we delete observations with missing prices or model names. This brings our overall e-bike sample from 91,506 to 73,795 transactions. In the second step, we remove observations with extreme prices by trimming the tails of the price distribution at 2%, which gives us 68,149 observations.

Third, in order to be able to estimate the pass-through model, we require bike brand models to be sold throughout the full sample period. We also require there be a sufficient amount of bikes sold by each retailer for the estimation to handle fixed effects for both models and retailers. We initially identified 40 top selling bike models that were sold throughout the period for which we selected the top 50 retailers. One retailer only sold two retail-branded models, so we dropped the retailer and models from the sample.

We chose to focus on the top 50 retailers and 40 models in the data and since one retailer only sold two models, we drop those observations arriving at a sample of 38 models and 49 retailers with 20,585 observations for the time period January 2017 to October 2019. We match these e-bike observations to our subsidy sample and obtain a total number of 20,586 e-bikes. We use this data to graph Figure 2 and to specify the regressions in Table II.

A.2 Car Registry Data

This appendix presents more detailed descriptions of the car ownership data for individuals in the subsidy sample. The data is obtained from the Swedish Transport Agency delivered by Statistics Sweden.

Table A.2 presents a t-test that shows that the number of individuals and driving behavior among those who bought and sold cars are similar.

Table A.2: Driving Behaviour of Car Buyers and Sellers

This table presents the results of a t-test in means between the driving behaviour of car owners who sold their cars post-subsidy or non-car owners who bought a car post-subsidy. The dependent variable is VKT (Vehicle Kilometers Travelled) averaged over the pre- and post periods.

Group	Obs.	Mean	Std. error
Entering car owners	5,859	12,148.98	98.24
Exiting car owners	5,666	11,977.86	106.67
Combined	11,525	12,064.85	72.42
Diff.		171.12	144.86
		t = 1.1813	DF = 11,523
H_a: Diff. $\neq 0$		Pr($\|T\| > \|t\|$) = 0.2375	

Figure A.1 displays the mean VKT across car age. Year 0 represents cars purchased the same year and so does not have complete 12 month driving histories. Mandatory yearly inspection (and odometer VKT readings) is required from year 3. The Swedish Traffic Agency imputes VKT estimates for younger cars.

Figure A.2 shows a frequency plot of the mean pre-post difference in VKT across the sample of subsidy recipients. The difference is presented for both absolute as well as relative (adjusted for municipality average) VKT.

Table A.3 shows that subsidy recipients are significantly less likely to own a car if they live in urban areas, have short commutes, or good access to public transport. Car ownership is higher among older, higher-income individuals and households with children, while women and university-educated recipients are substantially less likely to own a car.

Figure A.1: Car Fleet: Car Age, Registry and Estimated Data

This figure displays the mean Vehicle Kilometers Travelled (VKT) from 2016 to 2019, indicated by the orange line, in relation to the age of a car. The light orange area shows a one standard deviation from the mean. Furthermore, this figure shows the age distribution of the car fleet of subsidy recipients indicated by grey bars.

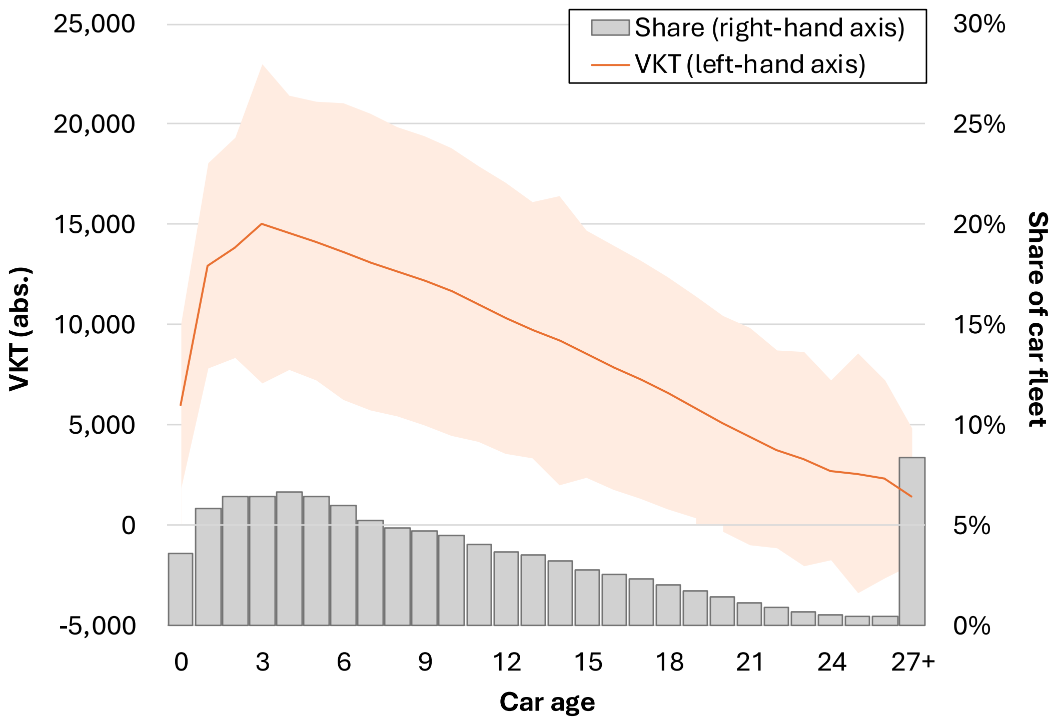

Figure A.2: Distribution of Pre-Post Difference in VKT

This figure displays distribution of the pre-post difference in VKT at the individual level. The changes are calculated over individuals who are both in the sample pre- and post subsidy. VKT was winsorised at the 1%-level. The difference in VKT is plotted both in absolute (grey area) and relative (orange area) terms.

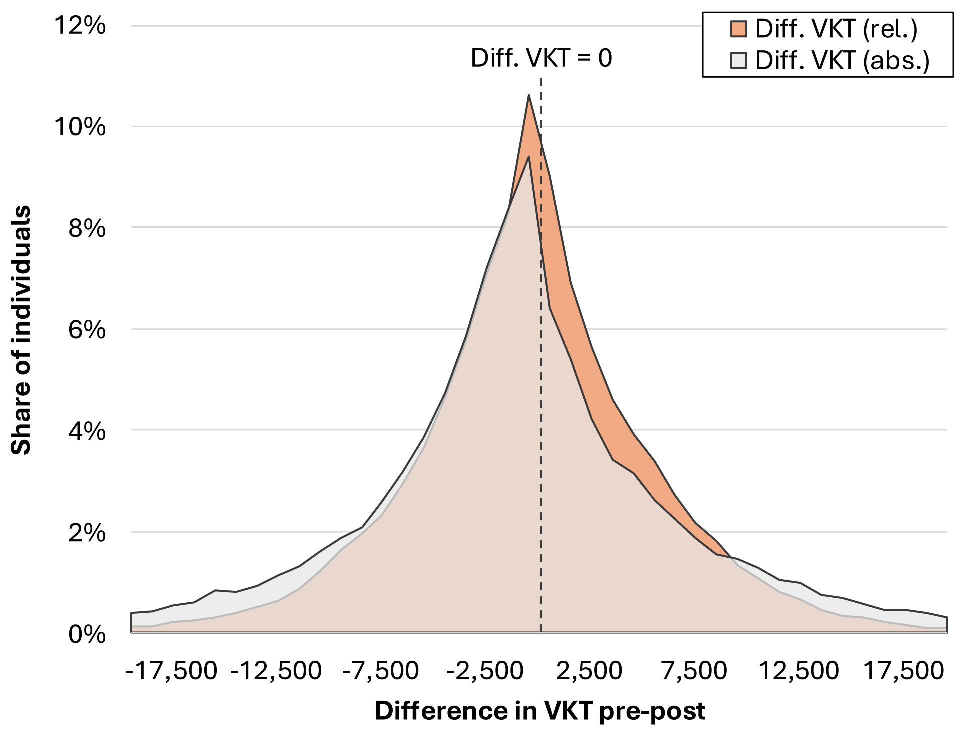

Table A.3: Car Ownership among Subsidy Recipients

This table reports marginal effects from probit regressions where the dependent variable is a dummy indicating the subsidy recipient owned a car in 2016 or 2017. Key independent variables include car ownership, residence in municipalities in the top decile of population density (urban), commuting distance of 5 km or less, and residence in municipalities in the top quartile of public transport density. Controls include high income (disposable income > 364,000 SEK), age, gender, university education, and the presence of children in the household. Robust standard errors in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)
VARIABLES	Car owner
Urban	-0.121***
	(0.007)
Short commute	-0.043***
	(0.006)
High public transport density	-0.059***
	(0.006)
High income	0.053***
	(0.006)
Age	0.009***
	(0.000)
Women	-0.253***
	(0.006)
Children	0.066***
	(0.007)
University	-0.049***
	(0.006)
Observations	27,628
Pseudo R2	0.132

A.3 Lifetime Reduction CO_2 Estimates

In order to calculate lifetime savings, we need to make assumptions about the lifetime of an e-bike. The European Cyclist's Federation (Blondel, Mispelon, and Ferguson (2011)) estimates the life-span of an e-bike to eight years and 19,200 kilometers, which is what we use when we scale the benefits of reduced emissions from driving. Since most driving reductions fall well below the lifetime distance limit, we do not add e-bike replacement costs and emissions for those who would be above the 19,200 kilometers limit.[17]

We aggregate CO_2 emissions from manufacturing and charging the e-bike with reductions from driving. We assume the manufacturing of an e-bike to produce 130 kilograms of carbon emissions of which the battery emits 34 kilograms. These emissions are calculated for a steel frame, but can be both much higher (if aluminium is used) or lower if the frame is made of carbon. To arrive at a comparable distance measure, they combine production emissions and life-cycle estimates (7 grams) with an additional 9 grams of energy consumption and 6 grams per kilometer for additional calories needed for biking to arrive at at total carbon emission of 22 grams per kilometer. Since Sweden has a cleaner energy mix compared to other countries and battery efficiency has become better, we use an online energy and emission calculator provided by one of the larger producers of e-bike batteries, Bosch. Using an estimate of an effective energy need of 5.9 watts per hour (Wh) per kilometer and 0.125 kilograms of carbon emissions per KWh, we arrive at a much more modest estimated 0.74 grams of CO_2-emission per kilometer. Combining the same emissions for production over the life-cycle (7 grams), additional emissions from driving (6 grams) with one gram of emissions related to electricity generation, the distance emission estimate we use is 14 grams per kilometer over the life-span of an e-bike.[18] When we apply our estimated emissions of e-bikes to our sample, we need to account for those who receives the subsidy without reducing their driving. We therefore split emissions into variable (consumed energy) and fixed manufacturing emissions.

[17] There is also an implicit assumption here that the policy does not change behavior "forever". We choose to limit the benefits only to the lifetime of the e-bike.

[18] Our lower estimate is consistent with that of Bosch who refer to the German , see https://www.bosch-ebike.com/us/service/sustainability. Our model would imply a per kilometer emission of 14.6 grams for the UK and 15.6 grams for the US corresponding to CO_2/Kwh electricity emissions of 0.256 and 0.429 kilograms.

A.4 Geographical Analysis

We collect regional data on Sweden's 290 municipalities available from Statistics Sweden, allowing us to analyze the e-bike subsidy take-up based on car use outcomes on an aggregate level. In addition, we create a panel of voting outcomes in the 2014 and 2018 for each 11,674 voting districts to test how e-bike take-up led to more or less political support for the Green Party that proposed the subsidy in front of the September 2018 elections. Table A.4 summarizes the key variables in the regressions presented in Table VIII in the main paper and below in Table A.5.

Table A.4: Summary Statistics Geographical Analysis

This table presents means (standard deviations) for the municipality and voting-district level analyses of e-bike adoption. The statistics are presented over the sample of 290 municipalities in 2018 and 5,837 voting districts in 2014 and 2018. The table denotes e-bike adoption defined as the number of e-bike subsidies scaled by number of inhabitants/ eligible voters (in thousands) and population density defined as the number of inhabitants/ eligible voters per square kilometer. Variables include the number of cars in 2018 scaled by thousands of inhabitants/voters (All Cars), measured separately for hybrid/electric (HEVs) and gasoline/diesel fuel powered cars (ICEVs). The table also reports the population/ voter share of women, young adults, individuals with higher education, foreign born, and the median log income.

	Municipality	**Voting district**
E-Bike Adoption	7.911	6.055
	(4.231)	(9.062)
Population Density	0.156	2.354
	(0.568)	(4.393)
All Cars	545.054	
	(66.192)	
ICEVs	511.443	
	(68.517)	
HEVs	10.615	
	(6.648)	
Women	49.204	53.234
	(0.763)	(2.698)
Young Adults	33.950	18.667
	(3.128)	(7.489)
Higher Education	12.464	27.503
	(5.024)	(12.604)
Foreign Born		12.131
		(12.159)
Median Income (Ln)	5.591	
	(0.095)	
Time	2018	2014 & 2018
Obs.	290	11,674
Scaling	Population	Eligible voters

We test the presumption that higher e-bike adoption is associated with a larger fraction of votes by merging e-bike subsidy sales on the voting district level with voting outcomes for the election in September 2018 and 2014. Formally, the panel regression model is

$$Votes_{i,t} = Adoption_{i,t} + \beta_j X_{j,i,t} + \gamma_t + \delta_i + \epsilon_{i,t}, \tag{A.1}$$

where $Votes$ denotes the fraction (expressed in percent) of votes for each voting district i during year t (i.e. 2014 and 2018). $X_{j,i,t}$ denotes a set of j voting district controls and γ_t and δi denote year and district fixed effects. The voting data is quite detailed with 5,837 voting districts in sample which we obtain from Statistics Sweden. The panel spans only two years, meaning that the e-bike density variable takes the value 0 for 2014 and a fraction of e-bikes subsidies for each voting district for 2018. Our main dependent variable is Green Party votes, but we also include far-right wing party Sweden Democrats (SD) and far left-wing Left Party (LP) for comparison and to understand to which extent there were complementarities or signs of polarization of the policy intervention (Stokes (2016)).[19] Statistics Sweden also maintain some characteristics of inhabitants on the voting district level. For both years, we obtain data on the population density (thousands of individuals per square kilometer), proportion of women and young adults (aged 18-28), higher education (university studies) and Swedish citizens with a foreign country of birth. Proportions are scaled with the number of eligible voters in each district.

[19]The Sweden Democrats was formed in the 1980's with close ties to the nationalistic neo-nazi movement. Initially they were primarily focused on opposing immigration, viewing it as a force that diluted traditional Swedish identity and values. It has since formulated a full-scale political agenda in opposition to mainstream policies on a wide range of topics, including EU membership, gay rights and climate change legislation.

Table A.5: Green Votes and E-bike Take-up

This table reports OLS panel regressions where the dependent variable in columns (1) and (2) is the percentage of votes for the Green party (GP) in parliamentary elections in 2014 and 2018. The dependent variable in columns (3) and (4) is the percentage of votes for the far right Sweden Democrats (SD) and in columns (5) and (6) the Left Party (LP) for the same elections. The independent variable is the number of e-bike subsidies scaled by number of voters (in thousands) as in Table VIII. The controls are district-level demographics that include the proportion of women, young individuals (aged 18-28), individuals with higher education and Swedish citizens with a foreign country of birth. All proportions are scaled by the number of eligible voters in a district. The population density is defined as thousands of voters over municipality area in square kilometers. All regressions include municipality fixed effects and a year dummy for 2018. The sample includes 5,837 voting districts based on the 2014 classification of voting districts. The constant is excluded from the table but included in the regressions. Standard errors in parenthesis are clustered at the municipality-level where *, ** and *** denote significance at the 1%, 5% and 10% level.

	GP votes (%)		SD votes (%)		LP votes (%)	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
E-Bike Adoption	0.023***	0.035***	-0.053***	-0.106***	-0.077***	-0.006
	(0.008)	(0.005)	(0.013)	(0.010)	(0.016)	(0.014)
Women		0.050***		-0.385***		0.067
		(0.016)		(0.040)		(0.063)
Young Adults		0.105***		-0.032**		0.245***
		(0.008)		(0.016)		(0.028)
Population Density		0.032		-0.090***		0.122
		(0.032)		(0.030)		(0.121)
Foreign Born		-0.040***		-0.073***		0.050***
		(0.006)		(0.008)		(0.016)
Higher Education		0.078***		-0.215***		0.042
		(0.012)		(0.019)		(0.029)
Year = 2018	-2.700***	-2.004***	5.403***	3.707***	0.784**	0.582**
	(0.190)	(0.204)	(0.306)	(0.304)	(0.358)	(0.280)
Observations	11,674	11,340	11,674	11,340	11,674	11,340
R-squared	0.590	0.711	0.680	0.791	0.492	0.603
Adj. R-squared	0.579	0.703	0.672	0.785	0.479	0.592
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A.5 presents the results. Columns (1) and (2) report specifications in which the dependent variable is the Green Party (GP) vote share, and the main variable of interest is e-bike adoption. Support for the Green Party is generally higher in voting districts with a larger fraction of women, younger voters, and highly educated residents. The coefficient on the year dummy is negative and close to 2 percentage points, reflecting the overall decline in Green Party support from 6.9% in 2014 to 4.4% in 2018.

We find that areas with higher e-bike adoption exhibit stronger support for the Green Party in the 2018 election, conditional on the 2014 election outcome. The estimated effect is economically meaningful: a one–standard-deviation increase in e-bike adoption is associated with nearly a one–percentage-point increase in the Green Party vote share.

In contrast, the estimated effects for both far-right and far-left parties are negative, suggesting that the relationship is specific to the Green Party rather than reflecting a broader leftward shift or increased political polarization.