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ARE E-BIKE SUBSIDIES COST EFFECTIVE IN MITIGATING CARBON EMISSIONS?

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Are E-Bike Subsidies Cost Effective in Mitigating Carbon Emissions? Anders Anderson, Harrison Hong, and Eline Jacobs NBER Working Paper No. 29913 April 2022, Revised April 2025 JEL No. H2, H20, H21, H22, H23, R4, R48, R49

ABSTRACT

E-bike subsidies are used in a number of large carbon-emitting countries. Evaluating their cost effectiveness in reducing emissions is more complicated than for other durable green goods since e-bike owners might not substitute away from driving. We evaluate a representative Swedish subsidy program by combining administrative, insurance, car registry and survey data. We find a complete passthrough of the subsidy to consumers, which incentivized a doubling of e-bike sales. For the 90,000 individuals in our subsidy sample, we find however only a small substitution from driving based on registry estimates, much smaller than reported by subsidy recipients in surveys. The cost of carbon would have to be\$800 per ton for the program to be cost effective. We also address additionality, coincidental benefits and alternative more cost-effective e-bike subsidy designs.

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Harrison Hong Department of Economics Columbia University 1022 International Affairs Building Mail Code 3308 420 West 118th Street New York, NY 10027 and NBER hh2679@columbia.edu Eline Jacobs Swedish House of Finance at the Stockholm School of Economics Sveavägen 65, SE-113 83 Stockholm Sweden eline.jacobs@hhs.se The transport sector is responsible for approximately one quarter of world greenhouse gas (GHG) emissions, making it a critical focus area for achieving the goals of the Paris Agreement. Within this sector, cars are responsible for around 60% of emissions according to the European and US Environment Protection Agencies, making transportation policy especially important to reach these mitigation goals¹.

Electric bikes (e-bikes) have emerged as a promising alternative mode of transport that can reduce emissions from short-distance trips traditionally made by cars. To promote the adoption of e-bikes, subsidies are used not only in Europe but in a number of other large carbon-emitting countries, like the US, China, and India (see Table I). Despite their growing popularity, the effectiveness of e-bike subsidies in reducing carbon emissions remains poorly understood. While surveys suggest that e-bike adoption can replace car trips, there is limited empirical evidence on actual behavioral changes and associated emissions reductions. Most importantly, existing studies often rely on self-reported data, which can overestimate the extent of substitution.

In this study, we evaluate a representative large-scale e-bike subsidy program that was implemented in Sweden in 2018. By combining administrative data from the Swedish Environment Protection Agency (SEPA) with car registry and insurance data, we track changes in vehicle kilometers traveled (VKT) among subsidy recipients and hence are able to address these challenging issues.

Our findings reveal a near-complete passthrough of the subsidy to consumers, resulting in a temporary surge in e-bike sales. However, the actual reduction in car use—as measured through registry data—was significantly smaller than self-reported estimates from surveys. We estimate the cost of carbon abatement for this program and find that the social cost of carbon would need to be approximately \$800 per ton for the program to break even.

Our results underscore the need for more targeted policy designs to maximize the carbon reduction potential of e-bike subsidies. Specifically, we propose that subsidies should be better aligned with actual car ownership and usage patterns, and potentially linked to verified reductions in driving behavior. This study contributes to the broader policy discussion on cost-effective climate solutions in the transport sector, highlighting the importance of evidence-based approaches in designing interventions to promote low-carbon mobility^{2,3,4,5}.

Main

We combine administrative, insurance, car registry and survey data from a large-scale, 3-year, one billion Kronas (around \$110 million) Swedish e-bike subsidy program that was implemented in 2018. The program was prematurely suspended after a change in political leadership following elections in 2018 at a cost of 370 million Kronas and 89,621 e-bikes sold. The subsidy covered 25% of the retail price, on average 4,113 Krona (\$463), with a cap of 10,000 Kronas (or around \$1,100) and was paid out directly to the consumer. The Swedish subsidy program was similar in structure to programs implemented and proposed across the world, as documented in Table I.

The subsidy was obtained by filing an application to the Swedish Environment Protection Agency (SEPA), which is our main data source that contains the identity of the recipient along with details of the purchase. By matching our subsidy data to the Swedish car registry, insurance data, and a survey solicited by SEPA, we estimate both the passthrough of the subsidy to consumers and the substitution away from car driving. We translate reduced driving to carbon savings to estimate the implied social cost of carbon, revealing the policy's cost-effectiveness in reducing emissions.

Incentivizing Purchases

To address whether the subsidy incentivized e-bike purchases, we must compare sales before, during and after the subsidy to infer the efficacy of the uptake, i.e. estimate the passthrough of the subsidy to consumers. We merge the subsidy data with sales data from Solid, the leading insurance provider for bicycles in Sweden (see Online Methods and Table OM.1 for additional details). Solid offers insurance at the point of sale of new bikes, covering approximately 90% of the specialized bicycle dealers. Around 50% of all new bikes sold in Sweden are registered with Solid and we find that 76% of all subsidized e-bikes were sold by retailers in the Solid sample. The subsidy program coincided with a temporary surge in purchase of e-bikes. Aggregate data suggest that total e-bike sales in Sweden grew from around 67,000 to 103,000 in annual terms between 2017 and 2018 reflecting a 70% year-on-year increase found in our insurance data. Our subsample of sales contains 20,586 e-bikes consisting of the top 38 models sold by the 49 largest retailers during 2017 to 2019.

Figure 1 here

Figure 1 provides a graphical representation of the e-bikes sold over time. We trace out the average price for bikes, where we hold model and retailer constant throughout. Although the average price of e-bikes rising from 23,000 Kronas (\$2,600) to almost 25,000 Kronas (\$2,800) by late 2019, no sharp price increase occurred when the subsidy was introduced. E-bikes are mainly produced in China and traded in US dollars, and are therefore subject to exchange rate conditions. We also plot the average \$/Krona exchange rate in Figure 1, which indicates that some of the price increase can be attributed to currency weakening.

We run formal passthrough regressions using on prices before, during and after the subsidy intervention in Online Methods. Passthrough is measured by regressing the transaction price net of the subsidy on the subsidy attached to that transaction^{6,7}. A slope coefficient of 1 indicates complete passthrough to consumers, while a coefficient of 0 shows no passthrough, with producers capturing all surplus by raising prices. We cannot reject the hypothesis of full passthrough at conventional significance levels, indicating consumers received the bulk of the subsidy. The regression results are presented in the Online Methods section Table OM.2.

Incentivizing Behavior

To assess whether the subsidy dis-incentivized car ownership or use, we introduce car registry data. This data allows us to track changes in driving behavior, or the total VKT, for each person owning at least one car. Car data is annual, so we analyze two periods: before (2016–2017) and after obtaining an e-bike (2018–2019). We average VKT across two years and estimate driving patterns of subsidy recipients who appear in both periods to reduce noise in the data (see Online Methods for additional details). Figure 2a plots car ownership from 2016 to 2019, with the subsample of car ownership rate in Sweden.

Figure 2 here

The registry data comes with features that need to be addressed. Figure 2b partitions car owners (labelled "All") into two smaller groups. Group two focuses on drivers who owned a car both before and after the measurement year. Excluding the first and last year of ownership ensures a full calendar year of use, reducing bias in the estimates. This second group, labeled "Ownership", includes 45,990 people. Group three focusses on drivers with older cars since VKTs are estimated, and not inspected, for the first three years after purchase of a new car. The third group "Age" narrows the sample to those with cars that are on average four years or older, resulting in a selection of 31,219 people. We use these three groups to assess the average reductions between the pre- and post period.

Figure 2c plots the average VKT for our full sample of car owners which fell from around 15.7k in 2016 to 14.7k kilometers in 2019. By using home and work coordinates, we estimate commuting distances on a subset of 27,628 individuals. To estimate yearly commuting distances, we use commuting days reported by the government agency Traffic Analysis⁸. Our commuting distance averages around 5,200 kilometers per year, accounting for approximately one-third of an individual's total driving distance.

Figure 2d plots driving distance relative to municipality averages obtained by the STA. As average driving decreased between 2016 and 2019 nationally, correcting for regional

trends in driving is important to minimize bias in estimates. While subsidy recipients drive on average more than their peers, we observe the relative VKT falling from 726 kilometers in 2016 to 436 kilometers in 2019.

Figure 2e plots the mean reductions over the three groups "All", "Ownership" and "Age". The average driving reduction for the full sample ("All") is 616 kilometers per year in absolute terms and 205 kilometers in relative terms. The "Ownership" group shows an insignificant increase in reductions of 682 (261) in absolute (relative) terms, though this change is not statistically significant. The third group ("Age") gives the highest estimate at an absolute (relative) reduction of 1,040 (590) kilometers per year.

Last, 2f plots the estimated CO_2 savings associated with the change in driving. We convert driving reductions to carbon savings by multiplying the average change in yearly VKT by the average carbon emissions per kilometer for a given car type as estimated by the Swedish Energy Agency⁹. We find CO_2 reduction estimates in the range of 89 to 152 kg per year in absolute terms. To estimate relative reductions, we calculate the municipal mean of carbon emissions per kilometer using the average fuel use of cars in a municipality. The relative reduction estimates are much lower ranging from 23 to 77 kg per year. This suggests that absolute reductions likely reflect a broader change in driving beyond the scope of the subsidy intervention.

Registry versus Survey Data

Previous US surveys^{10,11} estimate that substitution can result in an average reduction of 225 kg of CO_2 per year, although the savings span a range from 53 kg to 575 kg depending on driving behavior. A smaller Swedish survey¹² estimate the share of transport replaced by e-bikes can result in a yearly reduction of 272 kg to 394 kg of CO_2 depending on the number of biking days and location. By and large, carbon reduction estimates are elicited through surveys and generally find substantial substitution potential. Another approach to estimate reductions is by spatially simulating driving patterns, obtaining an upper bound for full substitution. Evidence from England shows that individuals in rural

areas have the highest reducing capabilities at over 750 kg CO_2 per year¹³ assuming car commuting is fully replaced by an e-bike.

We match a SEPA survey to our car registry data, yielding 1,028 participants. The survey asks about commuting distance and car usage frequency, not total driving distances. We calculate yearly commuting distance by multiplying weekly distances by average working weeks, aligning with Traffic Analysis estimates for the general population.

Figure 3 presents a cross-validation between self-reported survey- and registry driving estimates. Figure 3a plots the average VKT on record for the survey respondents amounting to 15,142 kilometers pre-subsidy and 14,442 kilometers post-subsidy. On average, the same individuals report commuting 170.7 (77.3) days per year before (after) they bought an e-bike, translating to approximately 3,419 km when accounting for commuting distance. These survey-based estimates are plotted in Figure 3b. Figure 2c highlights the differences between registry and survey estimated reductions, where registry-based estimates average at 700 km while survey-based estimates average at 1,736 km. This difference is highly statistically significant (t-stat=-4.048, p-value<0.001).

Figures 3c to 3e show VKT differences across substitution levels. Of 261 individuals who fully replaced car commuting with e-bikes ("Substituted all"), 751 reported partial changes in driving ("Substituted some"). Both registry and survey reduction estimates are larger for the group who reportedly gave up driving all together. Further, while survey-based estimates are consistently higher than registry estimates, this difference is only significant for those who report a change in driving, labelled "Substituted some" (the difference of 1,129 is significant with t-stat = 3.925, p-value<0.001). In contrast, there is no statistical difference between survey and registry estimates for those who claimed they fully substituted their commuting (difference of 773 is insignificant with t-stat = 1.417, p-value=0.157). In other words, we can only detect a discrepancy between estimates for those who continued driving, not among those who reported that they stopped all together.

Program Cost and Benefit

We conduct a cost-benefit analysis of a dollar's worth of e-bike subsidy, focusing on carbon savings from reduced car use. With complete passthrough, the impact on producer surplus is minimal, allowing us to focus on how a dollar subsidy changed consumer behavior in reducing car usage.

To calculate lifetime savings, we make assumptions about the lifetime and use of an ebike. The European Cyclist's Federation¹⁴ estimates that the life-span of an e-bike is eight years and manufacturing emissions amount to 130 kg per e-bike. We include emissions of e-bike use, or 0.0015 kg CO₂ per kilometer for charging the battery. We use an individual's estimated reduction in driving as an estimation of the distance travelled yearly by e-bike.

Figure 4 plots the aggregate emissions of manufacturing and charging e-bikes for all subsidy recipients along with emission savings for all car-owning recipients. Aggregate emissions savings are the product of the estimated yearly emissions savings (Figure 2e) and the number of car owners scaled by the estimated life-time of an e-bike. To retrieve the net lifetime savings, we subtract the aggregate emissions attributed to manufacturing and charging the e-bike for the entirety of the subsidy sample. We sort results based on the size of savings. For our narrowest estimate of emission savings, the net savings of the e-bike subsidy are negative. The additional estimates show net positive lifetime savings across a broad range, peaking at 51,590 tons of CO₂.

Figure 4 here

To relate the subsidy's cost to the benefit of reduced emissions, we calculate the implied shadow price for CO_2 emissions by dividing the net emissions savings by the program's total cost (369 million Krona or \$42 million). This gives the estimated dollar cost per ton of carbon emissions needed for the policy to break even. We do so in two ways: (1) for the full sample, acknowledging that around 40% of recipients did not own a car imposing a cost to the program with no associated benefit, and (2) by restricting our sample to car owners only, as if everyone owned a car. The results are presented as lines in Figure 4. The solid line in Figure 4 shows that the shadow price of carbon needs to be very high for all reduction estimates. The estimate that conditions on older cars is the most favorable estimate of carbon savings translating to a shadow price of around \$805 per ton (\$425 for car owners only). This price, however, is still inconsistent with any conventional estimates of carbon pricing.

To compare our main findings, we instead incorporate our survey-based estimates to assess the impact of using self-reported data on the perceived subsidy potential and cost-effectiveness. We repeat the calculation on net lifetime carbon savings using survey-based reduction of 1,700 kilometers found in Figure 3c. This translates into yearly CO_2 emissions savings of around 250 kg per year, which over the life-time of an e-bike would be associated with a shadow cost of carbon of around \$450 for the cost of the program to break even. This reduces to \$250 if it would be possible to target car owners only.

A few factors affect the robustness of our findings, detailed in the Online Methods. Our analysis assumes all consumers are additional, meaning they wouldn't have purchased the e-bike without the subsidy¹⁵. The SEPA survey shows that, at most, twothirds of purchases were additional. If adoption occurred without the subsidy for these two-thirds, the effective cost would rise by 50%, doubling the break-even social cost of carbon.

In theory, the policy may yield additional benefits like improved health, reduced traffic congestion, better transport access, and manufacturing benefits. However, the low substitution rates that we document suggest minimal health impact; and since uptake was higher in rural areas, congestion reductions are unlikely. Most recipients were older, middle- to high income car owners, reducing the need for accessibility support. Additionally, with most e-bikes imported from China, Swedish manufacturing saw little impact. While these additional benefits are minimal in Sweden, they might be higher where car ownership is lower, public transportation is overburdened, and local manufacturing may benefit from increased demand.

Discussion

Overall, our findings suggest that the Swedish e-bike subsidy implemented in 2018 was cost-ineffective in reducing carbon emissions. The discrepancy between registry and survey estimates highlights that self-reported measures can overestimate substitution. Our study shows that evaluating policies in the domain of personal transportation, where substitution is not guaranteed, is inherently difficult, even with detailed individual data.

Ineffective substitution between transportation modes likely contributed to the program's cost-ineffectiveness. First, a third of subsidy recipients did not own cars, making it impossible for them to substitute their diving for biking. Second, cars are rarely the sole transportation mode. Instead, e-biking often substitutes for normal biking or public transport. In the survey, respondents were asked about their substitution between modes of transport depending on season before and after the purchase of an e-bike. While e-biking replaces car transport by 29% (16%), e-bikes also replace 14% (9%) of public transport and 17% (9%) of regular biking in summer (winter). The share of e-bike usage is similar across rural and urban respondents, but those in rural areas replace 32% of their car driving with e-biking, compared to only 15% among urban respondents in summer. This aligns with the notion that the substitution capability of e-bikes is larger in rural areas.

The subsidy design and regulatory context likely also contributed to the program's cost-ineffectiveness. First, the subsidy may have been ineffective in driving substitution due to the absence of usage-based restrictions. Substitution is implicitly ensured when policy benefits are tied to actual usage. Second, Sweden has few fiscal policies aimed at (work-related) transportation, and those that do exist tend to incentivize car travel. Consequently, this car-favored fiscal system may have contributed to the low level of substitution. This underscores how well-intentioned green policies can be constrained by broader market structures and regulatory environments¹⁶. There might also be political incentives to design broad based subsidies as a means of vote getting as opposed to implementing cost-effective designs (see Online Methods for additional discussion).

Finally, we analyze a scenario in which work-related car transportation is fully re-

placed by biking. Assuming complete substitution of 5,200 kilometers per year (see Figure 2c), the potential emission reductions are much closer to prior spatial analysis studies at savings of 748 kg per year. In this scenario, the policy breaks even at a social carbon cost of \$79 per ton, matching common estimates¹⁷, if targeted exclusively at car owners. It is unclear whether an e-bike subsidy tied to commuting would be as popular and the program's impact on aggregate emissions might remain limited, even if cost-effective per household. We leave this line of inquiry for future research.

Inclusion and Ethics Statement

The authors confirm that there is no conflict of interest and take responsibility for the following: study conception and design, data collection, analysis and interpretation of results, and manuscript preparation. This project, no. P1237, is approved by Statistics Sweden standard procedures for handling identified individual data according to the ethical and regulatory standards set by Statistics Sweden.

Data Availability Statement

The subsidy data on e-bikes in this paper is a proprietary data set which was obtained from the Swedish EPA in identified form. Statistics Sweden matched subsidy data to individual administrative data and made an anonymized data set available for analysis through their mainframe computer platform MONA (Microdata Online Access). In MONA, users can process data online without the microdata ever leaving Statistics Sweden. Following a confidentiality assessment pursuant to the Public Access to Information and Secrecy Act, Statistics Sweden may release microdata for research and statistical purposes. Microdata refers to individual units, such as persons or enterprises. Once a request for release has been approved, the person responsible at the recipient is to designate the users who are to be granted access to MONA in order to access the released data. Municipality-level data and the Stata codes used in this project are available from the authors.

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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 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). Target for policy where (C) denotes individual consumers and (B) denotes businesses. Type of fiscal policy where (D) discount proportional to price, (FR) flat rate per unit, (L) government loans, and (TC) tax credit

Panel A: E-bike Programs								
Location	Type*	Discount	Target**	Max. funding	Tot. earmarked	Period	Participation	Requirements/ Remarks
National programs								
Sweden	D	25%	U	\$1,100	\$48 mn	2017-2018	97,000	\$113 mn planned 2018-2020
China	D	15%	U	\$70	n/a	2024-2025	1.38 mn in 2024	Trade-in scheme. Extended in 2025.
India	D	\$70/kWh battery	C 1	5% 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%	U	€400	n/a	2017-2027	n/a	Max $\in 2,000$ for cargo bikes.
Germany	D	25%	U	€2,500	€1 bn	2024	n/a	Suspended in 2024 due to budget freeze.
Italy	D	20%	U	€500	€125 mn	2020-2022	n/a	E-bikes, E-scooters, sharing services.
Luxembourg	D	50%	U	€600	n/a	2020-2022	n/a	One E-bike p.p.
Scotland	L/FR	n/a	C/B	€8,000	€1 mn/yr	2018-2024	193 projects	Suspended in 2024 due to budget freeze.
Regional programs								
Delhi, India	D	\$60/kWh battery	U	\$360	n/a	2025	n/a	
Gujarat, India	D	\$60/kWh battery	U	\$300	n/a	2025	n/a	100% road tax exemption.
Maharashtra, India	D	\$120/kWh battery	U	\$240	n/a	2025	n/a	50% road tax exemption.
Paris, France	D	50%	U	€500	€12.0 mn	2020-	est. 10,000	Provided by Île-de- France Mobilités.
Oslo, Norway	D	25%	U	\$600-\$1,200	\$1.2 mn	2016-2020	1,000-2,000	E-bikes/Cargo bikes.
British Columbia, CAN	FR	\$850 (CAD)	U	\$1,000 (CAD)	n/a	2019-	n/a	Mandatory car replacement.
California State, US	D	n/a	U	n/a	\$10 mn	2020-	n/a	CalBike and California Air Resources Board.
Utah, US	D	10% - 20%	U	n/a	n/a	Sep-Nov	43	Commercial discounts
Munich, Germany	D	20%	U	€500	n/a	2021-2024	n/a	Cargo-bikes.
Rome, Italy	D		U	€500	n/a	2020	est. 50,000	Bikes and e-scooters.
Wallon Brabant, Belgium	D	20%	C	€200	n/a	2020-2022	n/a	

Figure 1: 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 the main text (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.



Figure 2: Average Car Ownership, VKT and CO₂ Reductions in 2016-2019

This figure displays the registry data on car ownership and -use over the 89,621 recipients of the e-bike subsidy. Figure 2a presents the sample composition between car owners (blue line) and those without cars (light grey line) over the sample period, where the grey shaded area presents the post period (2018 and 2019). Figure 2b shows the share of "All" car owners pre and post (n=52,840) that fall into the groups "Ownership", owning a car in the years 2016 through 2020, and "Age", owning a car older than 3 years. Figure 2c plots the average annual Vehicle Kilometers Travelled summed (VKT) over an individual's cars. The dark shaded area presents the average commuting distance calculated based on the Euclidean distance between home and work coordinates and average travel days reported by Traffic Analysis. Figure 2d plots the average annual VKT relative to average municipal driving. Figure 2e plots the estimates of the difference in VKT before and after the subsidy over the samples "All", "Ownership" and "Age". The pre-post difference in CO₂ is calculated by multiplying the average change in yearly VKT by the average carbon emissions per kilometer to ra given car type as estimated by the Swedish Energy Agency. To estimate relative reductions, we calculate the municipal mean of carbon emissions per kilometer using the average fuel use of cars in a municipality. Figure 2f similarly plots the estimates of the difference in driving before emissions and after the subsidy. Light grey areas surrounding bars indicate 95% confidence bounds.



Figure 3: Registry versus Survey Reductions Estimates

This figure plots the results for a subsample of survey respondents that answered questions on their driving behavior before and after having obtained the e-bike, along with registry data on average VKT reductions before and after the subsidy. Figure 3a plots the recorded average driving distance for the group in the pre- and post subsidy window. Figure 3b plots the average reported commuting VKT inferred from a survey. Figure 3c plots the difference in VKT pre-post for the registry and survey data. Figure 3d describes a partition in which we group respondents those reported having given up commuting in their car all together ("Substitute all") and those who report having only changed their car use after the survey "Substitute some". Figure 3e and 3f plot the mean pre-post VKT differences for registry and survey estimates across these two groups. Light shaded areas surrounding bars indicate 95% confidence bounds. The sample contains 1,028 people.



Figure 4: 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). Italic 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.



Online Methods

This section presents the data matching procedure and complementary results to the analysis in the main paper. We begin by presenting details of the matching procedure between the subsidy data obtained from Statistics Sweden and the bike insurance data obtained from Solid and report the results of the passthrough regression where we infer to which extent the subsidy targeted consumers. We then present details of the car registry data obtained from the Swedish Traffic Authority, which Statistics Sweden has matched to our subsidy data. We also present an in-depth analysis of the survey data that allows us to address the issue of additionality. We end this section by an analysis of the uptake of e-bike subsidies across regions of Sweden as a function of car density as well as voting outcomes in the Swedish 2018 elections.

Insurance Data on Sales

The original data from Solid includes almost 700,000 observations of bikes sold and insured from January 2017 to October 2019 of which we can identify a subset of 91,506 e-bikes. Table OM.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.

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

Table OM.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.

		So	lid		SEPA
Sample	All	Before	During	After	During
(No. of months)	(34)	(9)	(13)	(10)	(13)
All bikes	695,587				
All e-bikes	91 <i>,</i> 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

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 choose 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 1 and to specify the regressions in Table OM.2. The final sample consists of 20,586 e-bikes of which 10,576

were sold during the subsidy period and 7,914 (75%) received a subsidy.

Estimating Passthrough

The passthrough analysis builds on an OLS regression analysis using e-bike model, retailer, county and time fixed effects⁷.

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 passthrough regression is then given by:

$$P_{i,j,r,t} = \beta_0 + \beta_1 Subsidy_{i,j,t} + \beta_2 Customer Demo_i + \beta_3 Krona/\$ + \delta_j + \kappa_r + \nu_t + \epsilon_{i,j,r,t}$$
(OM.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 passthrough, 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 OM.2. In the first column, we report the results with just model fixed effects, which controls for the impact of quality differences in e-bikes sold. We see that the coefficient of interest is -1.021 but is only mildly significantly distinguishable from one ($\beta_1 = -1$). The *p*-value from a *t*-test is 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. Columns (2) and (3) introduces time fixed effects instead of the exchange rate as time controls, and column (3) also control for in which county the consumer lives. The coefficient of interest is indistinguishable from 0 with *p*-values at any conventional level at 0.43 and 0.48.

Table OM.2: 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			

Car Registry Data and VKT

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 (2016 to 2019). We exclude individuals with a subsidy amount of zero, or a subsidy amount that is either less than 5% or more than 30% of the purchase cost. This provides us with a sample of 89,621 individuals. We find that 52,840 individuals (59%) in our e-bike data owned a car both before and after obtaining the subsidy 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. VKT is based on readings from vehicle inspection, hence the data is a reliable source for measuring total driving distance. New cars must be inspected for the first time 36 months after purchase. The STA estimates driving distances for newer cars when inspection-based data is unavailable.

To give an overview of car ownership and driving, we aggregate the individual VKT and estimate average commuting distance for our subset of car owners. 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). To estimate yearly commuting distance, we make use of estimated commuting days by commuting distance reported by the gov-ernment agency Traffic Analysis. This mainly adjusts for the fact that people with very long commuting distances typically commute fewer days. Eurostat mobility statistics find that 27% of daily travel distance is for work in Germany, but higher for more sparsely populated countries, see Transport statistics at https://ec.europa.eu/eurostat/statistics-explained.

Table OM.3 reports car ownership among subsidy recipients in addition to the average VKT per individual over the sample period. The aggregate data give three important insights. First, car ownership is very stable over time with around 54,000 people in sample owning cars every year. Second, the mean VKT is decreasing over time. As this general development is unlikely to be an effect of e-bikes only, we also benchmark individual VKT in our data to 290 municipalities averages that has been computed for us by STA. This allows us to benchmark VKT closer to the driving behavior at the local level.

Before analyzing individual driving behavior, we need to impose some assumptions on the car registry data. First, we exclude car owners that own a car either in only the preor the post period. These individuals do not affect aggregate VKT estimations as the driving behavior of non-car owners buying a car in the post-period is similar to the behavior of car owners in the pre-period selling in the post-period. Second, we do not have data to measure the counterfactual behavior of households that did not receive the subsidy. Our analysis of reduced driving is done on the aggregate level, treating any reduction as being all attributed to the intervention. We calculate individual VKT both in absolute terms as well as in relative terms with respect to municipality averages. Although both procedures are imperfect measures of reduced driving, they should represent upper bounds of any driving reductions following the acquisition of an e-bike. Second, 28% of people in the sample own more than one car in which case we opt to sum VKT across all vehicles, but obviously, they may be used by other individuals in the same household. Our main goal of our analysis is not to measure the level of distance travelled, but to capture the change in driving behavior before and after the subsidy. Hence, we think our aggregation is reasonable given that also the e-bike should be available to those using the car at the household level.

There are two concerns when using Swedish car registry data to assess changes in driving behaviour. To start, during the first three years of having purchased a new car, individuals are not required to register their mileage. Hence, the STA provides estimations on mileage in the first three years of use (see Figure OM.1). While this might skew our results, the share of newer cars in our sample is low. The average car in the sample being over 11 years old. Hence, the majority of data points are based on actual inspection data rather than being estimations. Second, registry mileage does not reflect the change in car ownership during the year. This is especially important when an individual buys a car, without having owned a car before, or when an individual gets rid of their car(s). These "first" or "last" years of ownership may over- or under-report the individual's actual mileage. When assessing the change in VKT, we take these concerns into account by first, restricting our sample to individuals with non-estimated registry data, and second, by excluding "first" or "last" years of car ownership from our sample.

Table OM.3 reports car ownership among subsidy recipients in addition to the average VKT per individual over the sample period. Table OM.4 presents a t-test that shows that

the number of individuals and driving behavior among those who bought and sold cars

are similar. Figure OM.1 displays the mean VKT across car age.

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

This figure displays the mean Vehicle Kilometers Travelled (VKT), indicated by the orange line, in relation to the age of a car based on car data from 2016 to 2019. 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 over the years 2016 to 2019 indicated by grey bars.



Survey versus Registry Data

This appendix presents details of the survey data and how it is matched to registry car data. Table OM.5 presents a cross-validation between self-reported survey- and registry estimates. 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 OM.5 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

Table OM.3: 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 preand 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 Engine 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 ow	nership (full sample)					
		Pre-si	ubsidy	Post-s	ubsidy	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	<u>10,916</u>	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	
Type	ICEV's	71,520	72,201	71,868	71,263	
$\Delta \sigma o \int$	\leq 3 years	16,850	18,361	18,610	17,763	
Age)	> 3 years	59,626	59 <i>,</i> 128	58,903	59 <i>,</i> 589	
Panel B: Individ	lual VKT (car owners)					
		Pre-si	ubsidy	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

Table OM.4: 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 postsubsidy 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

of car-owning survey respondents to cross-validate our registry estimates.

Panel B of Table OM.5 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.

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 by estimating the average commuting days as a function of distance to work. We find the self-reported number of commuting days to be almost identical. The self-reported

Table OM.5: 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 ownershi	p (survey sample)		
Respondent	s 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: Cro	ss-validation surve	ey-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 (ca	ar owners)		
Reported substitution		Some	All	Some-all diff.
Pre-post diff	E. 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	

commuting distances are lower than what we estimate in the full sample, but this could be explained by the composition of the survey sample. Therefore, the extrapolation from commuting days seems reasonable, even if the methodology is somewhat generalized.

Finally, Panel C of Table OM.5 examines the gap between self-reported data and registry data. A subset of respondents (267 individuals or 26%) 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.

Additionality

This appendix analyzes the issue of additionality by using survey data obtained from the Swedish Environmental Protection Agency. question "How important was the subsidy for your decision to buy the electric bike?". Possible answers are graded on a five-point scale ranging from "Not important at all" to "Crucially important". Figure OM.2 summarizes the survey 3,523 responses to this question.

About 61% of survey respondents find the subsidy to be important (corresponding to those responding with 4 or 5). 16% responded that it was not important for their purchase (those with 1 or 2). 23% of the people said it was somewhat important (those who

Figure OM.2: The Importance of the Subsidy for Purchase

This figure displays the number of responses to the question "How important was the subsidy for your decision to buy an e-bike?". Possible responses ranges from "Not important at all" (1) to "Crucially important" (5); (6) denotes "Don't Know".



answered with 3). Six people responded that they did not know. We check whether this estimate differs across those 1,944 people who also reported how they commuted in more detail, and the fraction of people who reported that they used a car before they acquired the e-bike through the subsidy. The fraction is slightly higher ranging from 64% to 67%.

Table OM.6 presents OLS regressions where the dependent variable ranges from 1 (not important) to 5 (crucially important). We omit the six "Don't Know" responses from the analysis. We find that income, age and being female is negatively related to the importance of the subsidy for purchase. Column (6) includes self-reported commuting distance which is an insignificant determinant of subsidy importance.

Table OM.6: The Importance of the Subsidy for Purchase

This table reports OLS regressions where the dependent variable is based on the question "How important was the subsidy for your decision to buy an e-bike?". Possible responses ranges from "Not important at all" (1) to "Crucially important" (5). There are N = 3,523 responses to this survey question: 253 in group 1; 321 in group 2; 799 in group 3; 1,191 in group 4; 929 in group 5; and 6 reported that they did not know (omitted). Independent variables include log of household income, age and dummy variables taking the value one for women and university education; zero otherwise. Public transport denote the number of bus stations in the municipality. Column (6) includes the log of self-reported commuting distance based on 2,594 survey responses. Robust standard errors within parenthesis where *, ** and *** denote significance at the 1%, 5% and 10% level.

	"How in	portant wa	as the subs	idy for you	r decision	to buy an E-bike?"
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Log family income	-0.084**	-0.086**	-0.095***	-0.095***	-0.097***	-0.073
	(0.033)	(0.034)	(0.036)	(0.037)	(0.037)	(0.051)
Age		-0.011***	-0.010***	-0.010***	-0.010***	-0.008***
		(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Women			-0.129***	-0.130***	-0.131***	-0.173***
			(0.040)	(0.040)	(0.040)	(0.045)
Children			0.067	0.067	0.062	0.029
			(0.049)	(0.049)	(0.049)	(0.054)
University				0.004	0.009	0.013
				(0.042)	(0.043)	(0.050)
Public transport					-0.007	-0.008
					(0.005)	(0.006)
Log distance						-0.014
						(0.024)
Constant	4.169***	4.730***	4.779***	4.777***	4.820***	4.685***
	(0.211)	(0.226)	(0.227)	(0.228)	(0.230)	(0.299)
Observations	3,517	3,517	3,517	3,517	3,517	2,594
R-squared	0.003	0.018	0.021	0.021	0.022	0.016

Traffic Congestion

We collect geographical data on Sweden's 290 municipalities available from Statistics Sweden, allowing us to analyze the e-bike uptake 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 uptake led to more or less political support for the Green Party that proposed the subsidy in front of the September 2018 elections. Table OM.7 summarizes the key variables in these regressions.

Congestion is analyzed by comparing the uptake of e-bike subsidies and car ownership across geographic areas. We run e-bike adoption across Sweden's 290 municipalities on the following variables: population density, car ownership with controls and fixed

Table OM.7: Summary Statistics Geographical Analyses

This table presents summary statistics 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 (based on the 2014 classification of voting districts). 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 kilometre. 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
Ohs	290	11 674
Scaling	Population	Eligible voters

effects for the 21 counties. The regression is

$$Adoption_{i} = \alpha + \beta_{1}Population_{i} + \beta_{2}Cars_{i} + \beta_{i}X_{j,i} + \delta_{c} + \epsilon_{i}, \qquad (OM.2)$$

where *i* denotes municipality. *Adoption* is measured as the number of e-bike subsidy payouts per inhabitant and *Population* is measured by thousands of inhabitants per square kilometer. Controls include average age, median income and fraction of university educated and δ_c denote a dummy that takes the value of one for the county in which the municipality belong; zero otherwise. All independent variables are values at the end of

Table OM.8: E-Bike Uptake

This table presents the results of a regression where the dependent variable is the number of e-bike subsidies scaled by number of inhabitants (in thousands) in each of the 290 municipalities of Sweden. Independent variables include the number of cars in 2018 scaled by population (in thousands), i.e., All Cars, measured separately for hybrid/electric (HEV's) and gasoline/diesel fuel powered cars (ICEV's), and population density defined as thousands of inhabitants over municipality area in square kilometers. Control variables include the population share of women, young adults, individuals with higher education and the median log income. County FE denotes control variables for each of the 21 counties the 290 municipalities belong. Robust standard errors are reported within parenthesis where *, ** and *** denote significance at the 1%, 5% and 10% level.

		E-bike Ad	doption	
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)
Constant	-58.292***	-57.155***	-47.653**	-43.581**
	(21.217)	(20.913)	(21.126)	(20.989)
Observations	290	290	290	290
R-squared	0.689	0.688	0.693	0.707
County FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

2018. Table OM.8 presents the results.

The results are presented in Table OM.8 where we focus on the main variables of interest for brevity. Column (1) shows that the e-bike subsidy uptake across municipalities is negatively related to population density. The uptake was not mainly in the big city areas. Column (2) and (3) shows that the uptake is negatively related to car density, even when controlling for population density. A one standard deviation increase in car density paired with the estimated coefficient in column (3) is associated with a 0.59 decrease in e-bike adoption. This corresponds to a 7% decrease in the mean e-bike adoption of 7.91 bikes per thousand of inhabitants. Finally, column (4) splits the car variable in two and analyzes the relation for combustion cars (ICEV's) and hybrid cars (HEV's) separately. We find that e-bike uptake is even smaller in areas where combustion engine cars are more prevalent, but larger in areas where there are more hybrid cars.

To sum up, we do not find it likely that the subsidy had any notable effects on congestion, as the subsidy targeted people in areas with lower population density and car ownership. We find that uptake was considerably higher in areas wither higher green adoption as evidenced by hybrid-electric cars. This suggests that e-bike conversion to some extent targeted those who were already prone to convert to greener alternative transportation alternatives.

Votes

We also test the presumption that higher e-bike adoption is associated with a larger fraction of votes by merging e-bike subsidy sales on 11,674 voting districts for the elections in September 2018 and 2014. Formally, the OLS panel regression model is:

$$Votes_{i,t} = Adoption_{i,t} + \beta_j X_{j,i,t} + \gamma_t + \delta_i + \epsilon_{i,t},$$
(OM.3)

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 (which is generally considered to be a left party), 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

Table OM.9 presents the results. Column (1) and (2) report the results for a specification where the dependent variable is the percentage vote to the Green Party (GP) and the main variable of interest is e-bike adoption. Votes for the Green Party is generally higher in voting districts with a higher fraction of women, young and highly educated. The negative coefficient of the year dummy is around 2% and reflects the general decrease in support for the Green Party from 6.9% in 2014 to 4.4% in 2018.

A one standard deviation increase in e-bike adoption for the estimate in column (2) corresponds to a 0.32% higher fraction of green votes compared to the mean voting share for the Green Party of 4.21% in 2018. A one standard deviation increase in e-bike adoption is therefore associated with a 7.6% increase in GP votes.

Columns (3) through (6) present the results for the Sweden Democrats' (SD) and Left Party (LP) votes. Votes for SD are higher for older men living in rural areas and with lower education¹⁸. SD gained considerable support among voters in the 2018 election as indicated by the year dummy. Higher LP votes are more likely to be populated by young and foreign born citizens. We find that e-bike adoption is generally negatively related to both SD and LP votes belonging to the far right and left on the political scale.

Our results indicate that e-bike adoption is associated with significantly stronger voting support for the Green Party, though the effect is too small to counteract the overall decline in their votes during the 2018 elections. The increased support is specific to the Green Party and does not extend broadly to left-wing voters. Additionally, we find no evidence that the policy heightened political polarization, as e-bike adoption rates are lower in areas where support for the SD has grown.

Table OM.9: Green Votes and E-bike Uptake

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 OM.8. 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. Standard errors in parenthesis are clustered at the municipality-level where *, ** and *** denote significance at the 1%, 5% and 10% level.

	GP vo	tes (%)	SD vo	tes (%)	LP vot	es (%)
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)
Constant	6.633***	-0.165	12.949***	42.222***	12.432***	1.849
	(0.056)	(0.835)	(0.100)	(2.121)	(0.123)	(2.651)
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