Preference Malleability When Sustained Information and Experience Interact: Evidence from Bus Electrification

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Abstract

While accelerating the green transition demands broad public backing, governments often struggle to effectively connect large-scale infrastructure investments to tangible benefits for the taxpayers funding them. We study whether sustained communication can shift citizen attitudes, preferences, and behavior, in the context of public bus electrification in Singapore. In an RCT with 1,200 households in a neighborhood served by electric buses, half of participants watched video clips across seven encounters highlighting both private and social benefits of electric relative to diesel buses. The video treatment significantly raises satisfaction with electric buses across six co-benefit dimensions, with effects that build gradually and persist through the endline; information provision is most effective among initially skeptical participants and complements direct experience with the technology. Choice experiments administered repeatedly over the campaign show that the treatment increases willingness to pay for electric buses by 11 US cents per trip—10% of the average fare, or about one minute of walk time in Singapore's hot climate. Farecard-linked ridership data confirm that stated-preference shifts translate into behavior: treated participants persistently increase electric-bus use through intra-modal substitution, with the strongest effects among the majority without cars and those living near highly electrified bus services. The treatment also shifts general environmental attitudes beyond the transport domain among participants with direct experience of the cleaner technology. Governments that invest in green infrastructure but fail to communicate its co-benefits may forgo the broader self-reinforcing public support that such investments can generate.

Keywords. Green infrastructure, public support, sustained information campaign, randomized controlled trial, willingness to pay, stated and revealed preferences, urban transport

JEL codes. C93, D12, D83, Q51

Data, code, prespecified design, media, and ethics statements. We will deposit the anonymous household panel data collected in this study and the computer code to enable the replication of results; public-transport ridership data (Section 5) are proprietary and can be accessed through the LTA. The NUS Institutional Review Board Participant Information Sheet (including compensation) shown to, and Consent Form completed by, participants in the household panel are accessible here (Google Drive). See here for the questionnaires we administered at each of seven encounters. The purchase order with market research firm Blackbox Research Pte Ltd, prespecifying the research design (PO 5117150375 issued 10 September 2021), is here. The video clips used in the video treatment are viewable here (YouTube). The opinions are solely those of the authors and do not necessarily reflect the positions of their currently and formerly affiliated institutions, including the LTA and the CAAS.

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"Protecting our climate is in our hands, as is preserving our rainfall and our sea level. One great way to do this is to use cleaner buses. Each year, one electric bus releases 100 tons of CO_2 compared with 200 tons of CO_2 for a diesel bus. Electric buses release only half the CO_2 compared with diesel buses. Electric buses protect our climate. Electric buses have no tailpipe and no fumes. Less PM2.5 in our neighborhood protects our lungs. Electric buses are quieter. Less noise in our neighborhood protects our mental health. Electric buses are more expensive to buy but they break down less and are cheaper to run. Over time, they are a good investment. Singapore has 4,000 buses, which means we can save the equivalent CO_2 that is stored in 40,000 trees, every year, which is a lot of trees."
Text narrated over a seventh video that summarized and closed a series of clips shown to the treatment group, as part of our sustained education campaign.

1 Introduction

Governments worldwide are investing in green infrastructure—from renewable electricity grids to cleaner public transport fleets—yet public support for these investments often lags behind their social returns. A better-informed citizenry that understands the private and social co-benefits of cleaner production will express a clearer mandate to policymakers to sustain and accelerate such investments. If limited awareness is a barrier to public acceptance, low-cost informational campaigns may provide a scalable tool for building support and facilitating welfare-improving technological change. But how should governments communicate? Does communication work—not just in shifting what citizens say, but in shifting what they do? And does experience amplify the communication effect?

We study these questions in the context of urban bus electrification, a green infrastructure investment that is both globally significant and locally salient to the hundreds of millions of urban residents who ride public buses, and the many more living and working by dense urban roads. The land transport sector is a major contributor to climate change and air and noise pollution in cities worldwide (He et al., 2019; Liang et al., 2019; Holland et al., 2021; Alexander and Schwandt, 2022; Baran et al., 2025). Electric buses offer several co-benefits over the incumbent diesel technology: a sizable reduction in lifecycle greenhouse gas emissions after accounting for electricity generation and vehicle battery production; zero tailpipe emissions; noise reductions of up to 14 dB at the low speeds typical of urban

service (Laib et al., 2019; Glebe et al., 2024); and 25% lower maintenance costs owing to the simpler mechanical design of electric motors (Borén, 2020).[1] These co-benefits span the environmental, health, amenity, and fiscal domains, yet taxpayers may be largely unaware of them—particularly those who have not experienced the cleaner technology.

We implemented a randomized controlled trial with 1,200 households in a Singapore neighborhood where electric buses had been operating alongside diesel buses for over one year. Half of the participants were randomized into a video treatment group that, over seven offline and online encounters from September to December 2021, watched short clips highlighting both private benefits (reduced noise, no diesel fumes) and social benefits (improved air quality, climate mitigation, lower maintenance costs) of electric buses. The non-video group completed the same activities—choice experiments, attitudinal surveys, shared farecard records covering bus and train travel—but saw no videos. The repeated, staggered design mimics how a government might communicate the returns on a public investment to citizens over time, rather than relying on a one-off informational nudge. Singapore is a well-suited setting: 58% of residents commute by public transport, with (diesel) buses the dominant mode (Census, 2020); land transport accounts for 15% of national carbon emissions, and visibly so to urban residents (NCCS, 2024); and while the government has now announced a full transition to cleaner-energy buses, the nation entirely depends on imported oil, predominantly from the Middle East.

Four features make our design and contribution distinctive. First, we engage participants repeatedly over several months, tracking how preferences evolve with sustained exposure—an empirical counterpart to the repeated communication through which policymakers build public support for clean infrastructure investments. Second, rather than taking preferences as invariant for counterfactual analysis (Moshary et al., 2025), we document that preferences are malleable (Mattauch et al., 2022; Creutzig et al., 2022), and that the change in preferences interacts with direct experience of the cleaner technology (Carattini et al., 2024). Third, we link shifts in stated preferences to shifts in actual commuting behavior using two years of farecard-linked ridership data, providing novel evidence that sustained and evidence-based educational campaigns can bridge the gap between policy support and real behavior. Fourth, effects persist beyond the campaign period, a result that few comparable information interventions have been able to assess.

[1] Based on an electricity grid still predominantly powered by natural gas, we calculate that in our urban setting one circulating diesel bus emits 201 CO_2eq tons per year compared to 94 tons for a battery electric bus on a lifecycle basis. Each electric bus in operation represents an *annual* emissions reduction equivalent to the carbon stored by ten large rain trees (Samanea saman) (Ramchunder and Ziegler, 2021).

We report four main findings. First, the video treatment significantly raises satisfaction with electric buses across six co-benefit dimensions: carbon emissions, air quality, noise, service reliability, environmental impact, and an overall index, with effects that build gradually and persist through the endline. Information provision reduces belief polarization: the treatment is most effective among initially skeptical participants, and direct experience with the clean technology complements rather than substitutes for information.

Second, to quantify the malleability of preferences, we designed two types of realistic choice experiments administered repeatedly over the campaign. In bus-type-time tasks, participants chose between bus trips that traded off engine type (bus technology) against travel time. In value-of-time tasks, they chose between regular and express services (both familiar), trading off time savings against higher fares. Jointly estimating a random-coefficients discrete-choice model on the stacked data, we find that the video treatment increases willingness to pay (WTP) for electric buses by 11 US cents per trip relative to the non-video group—10% of the average fare paid by the sample, or about one minute of walk time to the bus stop in Singapore's hot and humid climate.

Third, we test whether stated-preference shifts translate into behavior. For 588 participants who provided anonymous farecard numbers at recruitment, we observe public-transport use spanning periods before, during, and after the campaign. (Other participants either paid for public transport with bank cards, which we refrained from collecting, or commuted only by car.) Event-study estimates show a sustained increase in electric-bus ridership among treated participants, driven by intra-modal substitution—switching from diesel to electric buses on overlapping routes in a dense network—rather than inter-modal shifts from cars to public transport. This revealed-preference effect is strongest among participants without cars and those living near highly electrified bus services, and it persists beyond the campaign's end.

Fourth, we ask whether educating citizens about one green infrastructure investment, in public transport, shifts attitudes beyond that domain. The video treatment significantly raises a composite of general environmental attitudes—spanning stewardship, climate anxiety, intergenerational equity, public policy, and individual action—among participants living near electrified bus services, with the strongest effects in the middle of the attitude distribution. The increase in electric-bus ridership is also largest among those whose environmental attitudes improved the most. These results suggest that sustained, domain-specific communication of co-benefits, reinforced by direct experience, can broaden public support for environmental protection beyond the technology in which the investment is

made. Governments that invest in green infrastructure but fail to communicate its co-benefits may forgo the broader public support that such investments can generate.

Contribution to the literature. Our paper contributes to three strands of literature.

First, it relates to research on the welfare impacts of industrial policies promoting cleaner vehicles (Beresteanu and Li, 2011; Li et al., 2017; Clinton and Steinberg, 2019; Kiso, 2022; Barwick et al., 2024, 2025). These studies rely on observational approaches and focus on financial incentives; we implement an RCT (the gold standard of evaluation (DellaVigna and Linos, 2022)) to examine whether an information-based intervention shifts preferences and behaviors. Furthermore, much of this literature assumes stable preferences for counterfactual analysis (Moshary et al., 2025), and may thus misestimate welfare gains when preferences are malleable (Mattauch et al., 2022). We instead document how public investment in cleaner infrastructure, coupled with efforts to communicate its co-benefits, shifts the preferences of citizens who encounter the technology—and we track their learning and behavioral response over time (Carattini et al., 2024).

Second, we build on a literature studying whether educational interventions can promote public support for environmental policies and adoption of pro-environmental behavior. A growing body of work shows that information provision—via text or video—can shift beliefs and grow support for policies that face low acceptability due to misperceptions about distributional impacts (Dechezleprêtre et al., 2025) or limited economic literacy (Jiang et al., 2026).[2] Other research documents the role of information in driving green behavior.[3] We bridge public support and behavior: our sustained intervention, including carbon labels with local tree equivalents, influences both public support for clean infrastructure and actual choices within public transport. Crucially, we provide evidence that educational campaigns can close the gap between stated support and revealed behavior.

A third strand estimates the WTP for cleaner transport, particularly light vehicles, including how preference and attitudinal shifts interact with experience (Hidrue et al., 2011; Jensen et al., 2013, 2014; Mamkhezri, 2025). We estimate WTP for cleaner public-transport

[2]Other applications include carbon taxes (Carattini et al., 2017; Maestre-Andrés et al., 2021; Douenne and Fabre, 2022; Fang and Innocenti, 2023), congestion pricing (Baranzini et al., 2021; Arlinghaus et al., 2024; Carattini et al., 2025), and more broadly tax policy, trade policy, and inflation (Stantcheva, 2021; Giaccobasso et al., 2025; Stantcheva, 2022; Binetti et al., 2024).

[3]See studies on resource conservation (Allcott and Rogers, 2014; Ito et al., 2018; Burkhardt et al., 2019; Brick et al., 2023), low-carbon diets (Lohmann et al., 2022; Jalil et al., 2023; Beyer et al., 2024; Lohmann et al., 2024; Ho and Page, 2025), Pigouvian pricing (Hintermann et al., 2026), public transport (Gravert and Collentine, 2021; Gessner et al., 2024), carpooling (Kristal and Whillans, 2020), and personalized carbon tracking (Andersson and Nässén, 2023; Enlund et al., 2023; Goetz et al., 2024; Schleich and Alsheimer, 2024).

technology, assess how sustained information shifts preferences and attitudes, and—by linking stated preferences to farecard records—show that the education campaign persistently increases real-world use.

The remainder of the paper is organized as follows. Section 2 describes the RCT design and implementation. Sections 3 and 4 present effects on perceived benefits of and WTP for electric buses. Section 5 uses linked ridership data to examine behavioral responses. Section 6 examines how domain-specific education spills over to general environmental attitudes and policy support. Section 7 concludes.

2 RCT design and implementation

In fall 2021, we recruited 1,200 residents from different households in Bukit Batok, a residential neighborhood served since April 2020 by electric buses alongside established diesel buses. Enumerators sampled from 39 high-rise apartment blocks that are typical of Singapore at various times of day and on different days of the week.[4] Figure A1 shows the locations of these blocks and situates the area within Singapore.

When an enumerator knocked on a household's door and multiple adults were present, the enumerator asked to speak with the adult "whose birthday was earliest in the year." This person was designated the sampled household member (hereafter, the participant). Mean participant age was 40 years; half were female; two-fifths held a Bachelor's degree; half had electric buses serving a bus stop right by their housing block; and the mean number of cars per household was 0.4 (Table A1). When recruited at baseline, participants were unknowingly randomized with equal probability into a non-video group and a video education treatment group (hereafter, the video treatment, or treatment).

From September to December 2021, each participant was asked to complete seven study encounters. The first and last were longer sessions conducted in the participant's home by typically the same enumerator; the five interim encounters were completed online on participants' personal devices. The endline was completed by 996 participants (our contract prespecified $N = 1,000$ at closing, with 17% baseline-to-endline attrition).

Figure 1 describes the RCT design. Half of participants—those in the treatment group—watched a video clip at the end of each encounter, except at endline when they watched the video at the start (for that final video to potentially affect responses to the activities

[4]Our design was prespecified in a purchase order with Blackbox Research dated 10 September 2021 (see cover page for link). Sampling was subject to age, gender, dwelling type, and housing block quotas, to represent Singapore's population.

we administered before closing). Video content varied across the seven encounters but was identical for all treated participants within each encounter. Participants in the control group watched no videos. Thus, the two groups' experiences effectively began to diverge at the end of the baseline encounter, when the treatment group saw its first video.[5]

At baseline, each participant met with the enumerator for about 20 minutes. We described the study's purpose in broad, non-environmental terms ("to measure commuter preference for various travel modes"); obtained consent; collected individual and household demographics; recorded farecard numbers by photographing them (for farecard users); and conducted choice tasks. Only then did we elicit environmental beliefs and attitudes and ask participants to rate their satisfaction with diesel versus electric buses (and experience with the latter). Participants were told to expect invitations to five online rounds, spaced 2-3 weeks apart, before the in-person endline meeting.

A few weeks after baseline, each participant received an SMS, WhatsApp, or email—possibly followed by a phone reminder—with a personalized link to complete a first online questionnaire lasting about three minutes, and similarly thereafter. Participation averaged 72% per online encounter, similarly across the treatment and non-video groups.[6] To reduce time burdens and thus attrition, each online encounter repeated only one activity that was familiar from the baseline—value-of-time tasks in the first and fifth online rounds (with different attributes than in the baseline), bus-type-time tasks in the third round, and bus-type satisfaction elicitation in the second and fourth rounds (Figure 1).

In December 2021, enumerators returned to participants' homes to administer a 15-minute endline interview, using questions similar to those at baseline.[7] For their time, participants earned SG$15 for completing the baseline, SG$5 for each online round, and SG$25 for completing the endline, totaling SG$65 (US$48 at US$1 = SG$1.35), paid as physical supermarket vouchers, which Singaporeans deem almost as valuable as cash. To increase participation, we communicated from the start that all vouchers—except those earned and paid at baseline—would be handed over at the endline meeting. Moreover, at recruitment, participants were informed that a "Lucky Draw," with reasonable chances of winning an Apple iPad, would be held among diligent participants who completed all seven encounters (581 participants did so, and six won an iPad).

[5]Through the questions administered over the encounters, even control-group participants gradually learned about the private and social gains from transit bus electrification.

[6]Table A2 shows that treatment does not affect attrition or completion times over encounters.

[7]We were constrained to conclude the study by year-end because in 2022 the transit agency had scheduled the redeployment of the electric buses to test them under other routes' operating conditions.

Self-reported travel patterns. The demographic characteristics collected at the start of the baseline interview included self-reported urban travel (Figure 1, row 1). On average, participants reported traveling by motorized vehicle on four days in the preceding week and making four trips on a typical day (see Appendix A.1). Public transport (bus and train) accounted for 62% of trips and cars (owned, taxi, or private hire) for 27%. Table A1 shows no significant differences in self-reported travel between the video treatment and non-video groups (again, treatment began only as the baseline meeting ended and treated participants watched the first video).[8] We again surveyed travel patterns at endline.

2.1 Public bus choice experiments

To estimate WTP for electric buses, we designed two types of realistic choice experiments. In the baseline encounter—immediately after surveying travel (and similarly in the endline)—each participant completed four tasks, each presenting one choice situation: two situations of a first task type, followed by two situations of a second type. In each situation, participants chose between two alternative bus trips (A vs. B) according to their "personal preference." Participants were prompted to "choose truthfully which one scenario (trip A or trip B) you prefer. There are no right or wrong answers."

The first type of choice task involved trade-offs between bus type (diesel vs. electric) and travel time, and did *not* mention money (e.g., fares). The second type elicited the participant's value of time, allowing us to monetize differences in travel time and, when combined with the first type, differences in bus type. Figure 1 shows which short online rounds repeated each of these two task types.

These choice experiments capture the idea that service-quality attributes—such as components of travel time and bus type—enter travelers' generalized costs. Participants were asked to make trade-offs that reveal their preferences. The trade-offs were designed to be realistic, reflecting Singapore's dense public-transit network, which typically offers several alternative routes to the same destination with travel times within minutes of one another. Electric buses were already operating in the neighborhood, unlike in stated-preference studies conducted before a technology is implemented or among participants unfamiliar

[8] We also asked "When you travel by public bus, do you use a Phone App to check the arrival time of buses?" and "What do you think is the main engine type of Singapore's public buses?" We expected the second question, with a choice between Diesel, Electric, Hybrid, Other, and Don't Know, to be difficult. Most Singaporeans do not purchase motor fuel and may not distinguish diesel from petrol (petrol was not listed) or electric from hybrid. 64% correctly selected Diesel; 75% of public-bus commuters reported using an app to check arrival times.

with it. Figure A1 shows the route made by highly electrified bus service 944 (as many as 80% of observed rider trips on electric buses) and notes that a total of 67 bus services and three train stations served the area.

Bus-type-time choice task. In this task, participants chose between two bus trips to a common destination. We randomly varied walk time to the bus stop, bus type (diesel or electric), and/or in-vehicle ride time (seated), while holding wait time fixed as "similar" across alternatives to reduce cognitive load. The top panel of Figure 2 shows an example in which the three attributes vary across trips A and B. This task allows us to measure preferences for diesel versus electric buses in minutes of walk time or minutes of ride time. As noted, we excluded fares because doing so might draw attention away from other attributes, and because the Government had ruled out fare differentiation by bus type during a likely multi-decade transition away from fossil fuels.

Appendix A.2 describes the attribute-value distribution. In the choice situations of this type that were administered by an enumerator, at baseline and endline, 25%, 52%, and 23% of situations had exactly one, two, and three attributes vary across alternatives A and B, respectively. In the third online round—typically completed on a participant's phone—we further reduced cognitive load: 64%, 30%, and 6% of situations had one, two, and three varying attributes.

Value-of-time choice task. To estimate WTP for electric bus rides, the second type of task elicited participants' value of time in monetary units per minute of ride time. The bottom panel of Figure 2 shows an example. Participants again chose between two bus trips to a common destination, but here the trade-off was between a regular bus and a more expensive express bus. This scenario is not contrived; it is familiar to Singaporean commuters.[9] In this type of choice situation, exactly two attributes varied across trips A and B: ride time and fare. Appendix A.2 describes how we designed the attribute-value distribution to be realistic and to encompass the transit agency's value-of-time estimates (Hess et al., 2017).

2.2 Other baseline questions prior to video treatment

General environmental beliefs and attitudes. After the choice experiments in the baseline interview—and similarly at endline—participants were shown 13 statements (a) to

[9]Figure A1 notes 62 regular and five express bus services in the intervention area.

(m) designed to measure general-domain environmental beliefs, attitudes, and policy support. They were asked: "How much do you agree with the following statements on a scale of 1 to 5, with 1 being Strongly Disagree, 3 being Neutral and 5 being Strongly Agree?" Examples include: (a) "With our current lifestyles, humans are abusing the environment," (g) "I feel anxious about what global warming, climate change, and rising sea levels will do to us," and (i) "Actions to reduce our impact on the environment are very important for Singapore's shoppers to consider."

Table A3 lists all 13 statements in the order presented, their sources in the literature (e.g., Verplanken and Roy (2016); Deryugina and Shurchkov (2016)), and the distribution of baseline responses across the 1,200 participants. We construct a summary index of environmental attitudes at baseline, and again at endline, with weights given by the inverse covariance matrix of baseline responses (Anderson, 2008; Allcott et al., 2022). This improves efficiency by placing less weight on statements that are highly correlated with others. Prior to these questions, the enumerator had not referenced the environment.

Bus-type satisfaction. At this point in the baseline interview, all participants were introduced to the public-transport energy mix. The enumerator explained "Singapore's MRT trains run on electricity, whereas almost all its public buses use diesel fuel. Like the petrol used in cars, the diesel used in buses comes from oil," and then asked participants to rate diesel buses against electric buses, on a 5-point Likert scale, along six satisfaction dimensions: fumes, noise, environmental impact, service reliability, carbon emissions, and climate-change impact. We randomized the order of the comparison across participants (diesel vs. electric or electric vs. diesel).[10]

Our analysis codes the 5-point responses from -2 (Diesel bus is better) through 0 (Same) to 2 (Electric bus is better). At baseline, the share agreeing (versus neutral or disagreeing) that electric buses were beneficial was high for five of the six co-benefit dimensions (in the order shown to participants): less fumes (73%), quieter travel (67%), better for the environment (68%), less CO_2 released into the air (68%), and less climate change (66%).

In contrast, 65% perceived diesel buses as providing more reliable service. This is consistent with the overall diesel fleet—while tautologically older than the recently introduced electric buses—being relatively new and well maintained. Salvo and Wong (2026) report diesel bus ages for Singapore that average 5-6 years and that low congestion and

[10]Participants were randomly assigned to scales ranging from (e.g.) "Diesel less fumes" on the left to "Diesel more fumes" on the right or, with equal probability, to the reversed ordering. In subsequent encounters that repeated this question, we kept alternating the order within participant, to mitigate bias.

regular maintenance ensure that buses travel at stable speeds; buses are inspected every six months and receive a mid-life interior and exterior refurbishment, making older buses indistinguishable from new buses to the rider (LTA, 2019).

For each participant, we construct a summary index of electric-bus satisfaction by aggregating the six co-benefit dimensions, again using inverse-covariance weights (Anderson, 2008). We also asked whether participants could "name any public bus service numbers in Singapore that use electric buses" and whether they had "ever traveled on an electric bus in Singapore" (Appendix A.3). We repeated the satisfaction and experience questions in the second and fourth online rounds and at endline (Figure 1).

2.3 Video treatment started at the end of the baseline encounter

Participants were randomly assigned with equal probability into a video group or a non-video group.[11] Table A1 shows that the two groups do not differ significantly in baseline demographics. Treated participants saw the first video at the end of the baseline encounter, when the information they received began to diverge.

In the video series, the treatment received information on the social and private co-benefits of electrifying transit buses. After each video, treated participants answered a "quiz question" that was simple for an attentive viewer and therefore served as an attention check. The inaugural video focused on climate mitigation and introduced carbon labels; the quiz therefore asked two sub-questions: "How much CO_2 does one diesel (resp., electric) bus used in Singapore release in one year?" For each diesel/electric bus sub-question, participants chose among three alternatives in "tons of CO_2 released (a global warming gas)": {100, 200, I don't know}. Because participants might not understand what 100 tons of CO_2 represented, the video translated this quantity into raintree equivalents, at 10 tons stored per raintree. Table A4 shows that participants were generally attentive even without financial incentives for correct answers: e.g., about 90% correctly answered each sub-question at baseline (diesel bus = 200, electric bus = 100 tons of CO_2 per year).

Following the baseline video highlighting the climate benefits of electric relative to diesel buses, the five videos shown to treated participants in the online rounds (1) reinforced the climate benefit, (2) explained that buses emit less carbon per passenger-km than cars, (3) emphasized cleaner neighborhood air and public-health gains from bus electrification, (4) showed that electric buses were significantly quieter for riders and pedestrians,

[11] Pedagogical videos have been used to communicate policy details and unfamiliar concepts (Stantcheva, 2021, 2022; Fang and Innocenti, 2023; Arlinghaus et al., 2024; Dechezleprêtre et al., 2025).

and (5) explained that electric buses were cheaper to maintain because their engines have fewer moving parts. The endline video recapped all co-benefits, reinforcing the advantages of electric buses relative to conventional diesel buses for commuters, neighborhood residents, and citizens. The videos were designed in collaboration with a senior Singaporean NUS student majoring in new media and communications. While rigorous, they used plain language, tended to adopt a gain (rather than loss) frame, and included a touch of local humor (DellaVigna and Linos, 2022).

Summary of education variation: Across groups and over time. The bottom of Figure 1 states the co-benefit theme of each of the seven videos, and Table A5 reproduces the scripts and provides YouTube links. We emphasize that the non-video group was also influenced by the intervention, beginning with the questions (e.g., bus-type satisfaction) asked after the choice experiments at baseline and in subsequent encounters. In this sense, questions asked early at baseline—of both groups, before treated participants saw the first video—provide the purest control. Beyond this longitudinal variation, the treatment group's education exposure began to diverge cross-sectionally from the non-video group at the end of the baseline encounter, when it saw the first video.

2.4 Tracking public-transport ridership (including non-video group)

At baseline, 52% of participants provided public-transport farecard numbers, while 32% reported paying with bank credit/debit cards, which we did not record by design; a further 16% stated that they did not use public transport.[12] After the panel study ended, we extracted system-wide public-transport ridership for 588 participants whose farecards could be matched. These revealed-preference travel data, spanning April 2020 to March 2022, include one quarter beyond the December 2021 endline and are uniformly distributed across the video and non-video groups (Table A10).

The raw data are at the farecard-by-trip-segment level. A segment is defined as a tap-in and tap-out on a bus or at origin and destination train stations. For each segment, we

[12]The use of bank cards to tap in and out of public buses and train stations has grown since the technology was introduced in 2019 (Awang, 2019). We did not attempt to collect ridership linked to bank cards, as participants would be reluctant to share sensitive financial data. Farecard numbers ("CAN IDs"), by contrast, cannot identify their holder, and the transit agency agreed to extract ridership linked to them. Participants who used farecards were somewhat older and less educated than early adopters of bank cards (Table A11). The consent form stated: "Your personal data will not be shared with any government agency, except for the CAN IDs that you provide which will be disclosed to the Land Transport Authority (LTA) for the sole purpose of allowing the LTA to match each CAN ID to its associated public transport travel history."

observe departure and arrival times and locations. Buses account for 73% of segments and trains the remainder. For bus segments, we also observe the vehicle's license plate, allowing us to identify whether the bus was diesel, electric, or hybrid/other (a small number of hybrid buses also operated in Singapore).

We observe 435,362 trip segments charged to 593 farecards shared by 588 participants (some shared more than one card) over 730 dates. Enabled by a dense public-transport network, a trip often consists of multiple segments adjacent in time and location, for example, two consecutive bus rides, or a bus followed by a train ride. Indeed, 28% of trips combine bus and train segments, highlighting the connectivity role of buses to train stations—including bus service 944 (Figure A1). Following Fesselmeyer et al. (2024), we combine segments into a single trip if a segment's departure time is within 15 minutes of the previous segment's arrival time. The 435,362 trip segments then collapse to 282,240 trips.

Appendix A.6 describes patterns in the ridership data. Because participants lived in a neighborhood served by electric buses, trips that include an electric-bus segment account for 5% of all their Singapore-wide public-transport trips.

3 Effects on perceived benefits of electric buses

We begin by examining how the repeated encounters and video treatment shift satisfaction with cleaner bus technology.

3.1 Empirical strategy

Following McKenzie (2012), we estimate the regression model:

$$Y_{irt} = \beta T_i + \alpha Y_i^B + \Gamma' \boldsymbol{X_{ir}} + \lambda_t + \epsilon_{irt}, \tag{1}$$

where electric-bus satisfaction Y_{irt} for participant i in encounter r on date t is regressed on satisfaction at baseline Y_i^B (measured prior to the first video) and a treatment indicator T_i for random assignment to the video group. The coefficient β captures the average treatment effect of the educational videos on satisfaction. The vector $\boldsymbol{X_{ir}}$ includes controls for the order in which electric and diesel buses were compared, and an interaction between this order indicator and an indicator for an online encounter. We include fixed effects for encounter calendar date and start hour (λ_t) to account for potential time influences (e.g., holidays). Standard errors are clustered at the participant level.

To assess dynamic effects of the video treatment on electric-bus satisfaction, we estimate a dynamic version of equation 1:

$$Y_{irt} = \sum_{r} \beta_r T_i \times \mathbf{1}(\text{Round} = r) + \alpha Y_i^B + \Gamma' \boldsymbol{X_{ir}} + \lambda_t + \epsilon_{irt}. \tag{2}$$

The coefficient β_r measures the effect of treatment in post-baseline encounter r.

Finally, to explore treatment-effect heterogeneity attributable to differences in participant characteristics, we follow the Sorted Effects method (Chernozhukov et al., 2018). We introduce heterogeneity into equation 1 by estimating a fully interacted model between the video-treatment indicator and baseline and sociodemographic covariates:

$$Y_{irt} = \beta_1 T_i + \beta_2' \boldsymbol{Z_i} + \beta_3' T_i \boldsymbol{Z_i} + \Gamma' \boldsymbol{X_{ir}} + \lambda_t + \epsilon_{irt}. \tag{3}$$

$\boldsymbol{Z_i}$ is a vector of participant characteristics that includes baseline satisfaction Y_i^B, self-reported typical-day total trips, public-transport and car-travel shares, and the summary index of environmental attitudes, all measured at baseline. It further includes demographic covariates: participant age, gender, bachelor's degree, employment status, housing block proximity to stops served by electric buses, presence of children aged under six in the household, car ownership, and low-income status.[13]

The video-treatment effect on participant i's satisfaction is then

$$\Delta_i^Y = \frac{\partial Y_{irt}}{\partial T_i} = \beta_1 + \beta_3' \boldsymbol{Z_i},$$

where treatment heterogeneity is attributed to cross-sectional variation in $\boldsymbol{Z_i}$. Following Chernozhukov et al. (2018), for electric-bus satisfaction Y we estimate the distribution of Δ_i^Y across participants over a grid of percentiles, conditional on the covariate distribution μ_Z, denoted $\Delta_{\mu_Z}^Y(u)$, and compute uniform confidence bands using the Bayesian bootstrap.

For a given electric-bus satisfaction dimension (e.g., reduced carbon emissions), the Sorted Effects method identifies the characteristics of participants most and least affected by the video treatment, and tests differences between these groups. Based on the estimated distribution $\Delta_{\mu_Z}^Y(u)$, we focus on differences in characteristics $\boldsymbol{Z_i}$ between the 10%

[13] We did not ask participants for household income. Instead, we proxy income using features of Singapore's structured housing market. Specifically, we classify households as low income if they live in one- to three-room publicly developed flats, do not employ a domestic helper, and do not own a car (Salvo, 2020).

of participants with the strongest and the 10% with the weakest treatment effects:

$$\mathbb{E}(Z_i|\Delta_i^Y \geq \Delta_{\mu_Z}^Y(0.9)) - \mathbb{E}(Z_i|\Delta_i^Y \leq \Delta_{\mu_Z}^Y(0.1)). \tag{4}$$

We group the covariates $\boldsymbol{Z_i}$ into two families: baseline (pre-treatment) outcomes and demographic covariates. We compute covariate differences and construct both independent confidence intervals (uncorrected for multiple-hypothesis testing) and uniform confidence intervals that adjust the family-wise error rate within each covariate family.

3.2 Video treatment effects on electric-bus satisfaction

Figure A2 shows a clear upward trend in satisfaction with electric buses relative to diesel buses in the video-treatment group, compared with the non-video group, across all six co-benefit dimensions. While at a slower pace, the non-video group also comes to perceive electric buses more favorably over the course of the study, likely due to repeated elicitation of bus-type comparisons alongside questions on environmental attitudes. For a given co-benefit (e.g., service reliability), satisfaction with electric relative to diesel buses diverges between the video and non-video groups particularly after treated participants watch the video emphasizing that co-benefit (see endline, after the last online-encounter video emphasized service reliability).

Table 1 reports estimates from equation 1. The video treatment significantly improves satisfaction with electric buses relative to diesel buses across all six co-benefit dimensions. In panel A, average treatment effects range from 0.18 to 0.23 on the five-point Likert scale (columns 1 to 6), corresponding to 4-6% of the baseline mean. Column 7 confirms that treatment increases overall satisfaction by one-fifth of a standard deviation. Panel B reports effects on the probability of agreeing that electric buses outperform diesel buses: the video treatment raises agreement by 5-9 percentage points across dimensions, equivalent to 6-23% of mean perceptions at baseline. The largest effect is for service reliability—the one attribute for which a majority of participants at baseline disagreed that electric buses outperformed—suggesting participants updated their initially skeptical perceptions of electric-bus reliability toward levels consistent with Singapore's established, reliable, and relatively new diesel fleet.

Figure 3 shows the dynamics of belief updating in the video treatment compared with the non-video group. Satisfaction with electric buses rises after watching the first video at the end of the baseline interview and persists through the endline interview.

These findings provide economically meaningful evidence that repeated exposure to educational videos in a targeted domain can strengthen support for clean-energy investment. The effect is consistent with recent cross-sectional video interventions that raise public support for environmental policies, whether in targeted policy domains—such as road pricing (Arlinghaus et al., 2024)—or more generally by clarifying the distributional impacts of climate policies framed as green infrastructure, combustion-engine-car bans, and carbon pricing with transfers (Dechezleprêtre et al., 2025).

3.3 Heterogeneous shifts in electric-bus satisfaction

Figure A3 shows treatment heterogeneity using the Sorted Effects method. Strikingly, the videos raise electric-bus satisfaction across nearly all percentiles, with effects statistically significantly different from zero for most participants: 68% on reduced carbon emissions (in the first panel, the 95% confidence interval lies above 0 beyond the 32nd percentile), 80% on climate mitigation, 60% on less fumes, 74% on quieter travel, 71% on service reliability, 63% on environmental impact, and 79% for the overall satisfaction index.

Treatment-effect heterogeneity is significant for carbon emissions and fumes (lower bound at the 95th percentile $>$ upper bound at the 5th). Where does this heterogeneity arise for these co-benefit dimensions? Figure 4 plots covariate differences between the most and least affected participants. We note three findings. First, treatment effects are more pronounced for participants served by electric buses at their doorstep (whom we also observe to ride electric buses more often). This suggests that direct experience can mitigate concerns about policy effectiveness, and that information provision complements rather than substitutes for direct experience (Carattini et al., 2018; Libgober and Song, 2022; Carattini et al., 2025). Second, participants with lower baseline satisfaction regarding CO_2 pollution abatement are more responsive to the video treatment. Individuals starting from a more skeptical or neutral position may be more likely to update beliefs when presented with targeted, credible information (Dechezleprêtre et al., 2025). These results speak to the literature on how information affects public-opinion polarization (Allcott et al., 2020; Levy, 2021; Bowen et al., 2023). In our setting, information provision induces convergence in beliefs about electric buses. Finally, the video treatment generates larger effects among participants who are younger and/or employed, who may be more receptive to emerging technologies.

4 Effects on preferences for clean bus technology

Having established that the intervention (via environment-related questions) and, in particular, the video treatment shifted electric-bus satisfaction relative to the baseline interview, we now estimate WTP for electric bus rides from the choice experiments.

4.1 Structural demand for electric buses (conditional on taking the bus)

Model setup and identification. Three institutional features noted earlier add realism here: the dense public transport network; the fact that most trips by our participants include a public bus; and the fact that electric buses had been servicing their neighborhood for more than a year alongside diesel buses. The choice tasks exclude substitution across travel modes and instead isolate substitution across bus services. The experiment asks: how many minutes of travel time am I willing to sacrifice to catch my preferred type of bus, when travel time is priced at a level appropriate for me?[14] To measure preferences over bus types, we specify a random-coefficients discrete-choice model that captures the utility-maximizing choice between alternative bus trips $j \in \{A, B\}$ made by individual $i = 1, \cdots, 1200$ in choice situation/task t of round $r \in$ {baseline, online, endline}:[15]

$$U^r_{ijt} = \beta^r_{1i} electricBus_{ijt} + \beta_{2i} fare_{ijt} + \beta^r_{3i} rideTime_{ijt} + \beta_{4i} walkTime_{ijt} + \delta^r_{jt} + \epsilon^r_{ijt}, \quad (5)$$

where $electricBus_{ijt} = 1$ if alternative j is electric and 0 if it is diesel; $fare_{ijt}$ is the ride fare, converted from Singapore to US cents; $rideTime_{ijt}$ is in-vehicle ride time (seated); and $walkTime_{ijt}$ is time walking from the participant's residential block to the bus stop, with all times measured in minutes. The destination is identical across the two alternatives. The term δ^r_{jt} is an alternative-by-task effect that captures any tendency to choose the trip shown in the left vs. right column (Figure 2). For analytical convenience, idiosyncratic taste shock ϵ^r_{ijt} is assumed to follow a type-I extreme-value distribution and to be i.i.d. across participants, alternatives, and choice situations within a round and task type.

We allow sensitivity to bus-trip attributes to vary over the campaign as participants

[14] These experiments were not designed to capture whether the availability of electric buses makes residents more or less likely to substitute away from other travel modes.

[15] This section pools all online encounters into a single round, with six situations per participant (Figure 1).

engaged with the study, with video treatment T_i, and due to unobserved factors:

$$\boldsymbol{\beta_i} = \begin{pmatrix} \boldsymbol{\beta_{1i}} \\ \log(-\beta_{2i}) \\ \boldsymbol{\log(-\beta_{3i})} \\ \log(-\beta_{4i}) \end{pmatrix} = \begin{pmatrix} \boldsymbol{\beta_{10}} \\ \beta_{20} \\ \boldsymbol{\beta_{30}} \\ \beta_{40} \end{pmatrix} + \begin{pmatrix} \boldsymbol{\beta_{11}} \\ 0 \\ \mathbf{0} \\ 0 \end{pmatrix} T_i + \begin{pmatrix} \boldsymbol{\nu_{1i}} \\ \nu_{2i} \\ \boldsymbol{\nu_{3i}} \\ \nu_{4i} \end{pmatrix}. \tag{6}$$

Vector $\boldsymbol{\beta_k} = (\beta_k^{baseline}, \beta_k^{online}, \beta_k^{endline})$ includes round-specific coefficients. We allow preferences for bus type and ride time to vary across rounds, but assume time-invariant preferences for money and walk time. The round-varying means $(\boldsymbol{\beta_{10}}, \boldsymbol{\beta_{30}})$ absorb changes in preferences for bus type and ride time associated with repeated bus-satisfaction questions, or campaign-induced shifts in perceptions of the in-bus travel experience; we assess robustness to this specification. Vector $\boldsymbol{\beta_{11}}$ captures the effects of video treatment T_i on electric-bus preferences. Because treated participants viewed the first video at the end of the baseline encounter, after the first round of choice experiments, we set $\beta_{11}^{baseline} = 0$.

We hypothesize that the coefficients on fare, ride time, and walk time are negative, and thus assume negative lognormal distributions. The participant-specific vector $\boldsymbol{\nu_i} = (\boldsymbol{\nu_{1i}}, \nu_{2i}, \boldsymbol{\nu_{3i}}, \nu_{4i})$ collects random components that are multivariate normal with mean $\mathbf{0}$ and variance-covariance matrix $\boldsymbol{\Sigma_\beta}$. These components are i.i.d. across participants. The vectors $\boldsymbol{\nu_{1i}}$ and $\boldsymbol{\nu_{3i}}$, corresponding to bus technology and ride time, are drawn independently from round-specific distributions, whereas draws ν_{2i} and ν_{4i} do not vary across rounds. We further allow the random coefficients on ride time and walk time to be correlated, capturing an individual's joint distaste for both time-intensive activities, that is, $\text{corr}(\nu_{3i}^r, \nu_{4i}) \neq 0$, which measures the correlation between $\log(-\beta_{3i}^r)$ and $\log(-\beta_{4i})$.

The interpretation of the alternative-by-task effect δ_{jt}^r depends on task type. In the bus-type-time task, the attributes of bus trips A and B—displayed in the left and right columns, respectively—are randomized. In the value-of-time task, A and B are always ordered as regular and express bus trips. Thus, δ_{jt}^r captures any left-right bias in the first task, whereas in the second it also captures any intrinsic preference for regular versus express buses. We therefore allow different δ_{jt}^r by task type and, to account for contextual differences, further allow these parameters to vary across rounds. For identification, we normalize $\delta_{Bt}^r = 0$.

Let $\boldsymbol{\mathcal{T}^{BT}}$ and $\boldsymbol{\mathcal{T}^{VOT}}$ denote the sets of bus-type-time and value-of-time tasks, respec-

tively. We can then rewrite utility specification 5 by task type:

$$\begin{aligned} U_{ijt}^{BT,r} &= \beta_{1i}^{r} electricBus_{ijt} + \beta_{3i}^{BT,r} rideTime_{ijt} + \beta_{4i} walkTime_{ijt} + \delta_{j}^{BT,r} + \epsilon_{ijt}^{BT,r} \quad \text{if } t \in \mathcal{T}^{BT}, \\ U_{ijt}^{VOT,r} &= \beta_{2i} fare_{ijt} + \beta_{3i}^{VOT,r} rideTime_{ijt} + \delta_{j}^{VOT,r} + \epsilon_{ijt}^{VOT,r} \quad \text{if } t \in \mathcal{T}^{VOT}. \end{aligned} \tag{7}$$

Because the ride-time attribute is drawn from a different distribution across task types, $\epsilon_{ijt}^{BT,r}$ and $\epsilon_{ijt}^{VOT,r}$ may have different variances. Let $\zeta^{BT,r}$ and $\zeta^{VOT,r}$ denote the associated scale parameters.[16] Following approaches that combine stated- and revealed-preference data (Adamowicz et al., 1994; Hensher et al., 1998), we identify these scales by jointly estimating responses to both task types and imposing that, within a round, a participant's marginal utility of ride time is common across task types, $\beta_{3i}^{BT,r} = \beta_{3i}^{VOT,r}$.[17] This places preferences for bus technology on the same utility scale as the fare coefficient and thereby identifies WTP for an electric bus trip.

Because participants completed the choice tasks in rounds spread over several months, contextual differences may also affect the utility scale within a task type. The relative scale factor for round r relative to baseline, $\zeta^{BT,r}/\zeta^{BT,baseline}$, is identified from cross-round choice variation, under the assumption that round-level differences in the fare and walk-time coefficients are attributable to scale rather than preference shifts.

Model estimation. We pool choice-task data from all rounds and estimate the model jointly. The parameter vector $\boldsymbol{\theta} = (\boldsymbol{\beta}, \boldsymbol{\Sigma_\beta}, \boldsymbol{\delta}, \boldsymbol{\kappa}, \boldsymbol{\zeta^{BT}})$ is estimated by simulated maximum likelihood (Train, 2009; Hess and Palma, 2019). Appendix A.4 provides further details.

WTP for an electric bus ride by participant i in round r is then given by

$$WTP_i^r = -\frac{\beta_{1i}^r}{\beta_{2i}}, \tag{8}$$

noting that the two coefficients come from different equations (task types) of system 7, with identification relying on a participant's common preference for ride time across task types within a round. Given the restriction that the fare coefficient β_{2i} does not vary by round, variation in β_{1i}^r maps directly into variation in WTP for bus technology over the 3-month campaign.

[16] The variances of these EVTI error terms are $\frac{\pi^2}{6(\zeta^{BT,r})^2}$ and $\frac{\pi^2}{6(\zeta^{VOT,r})^2}$.

[17] An estimate of $\kappa^r = \zeta^{VOT,r}/\zeta^{BT,r}$ below (above) 1 implies that the value-of-time tasks contain more (less) unobserved variance than the bus-type-time tasks.

4.2 Video treatment effects on electric-bus preferences

Table 2 presents estimates of equation 5 using all choice-task data from 1,200 participants. Columns 1-2 report multinomial logit estimates, excluding the participant-specific random terms $\boldsymbol{\nu_i}$ in the $\boldsymbol{\beta_i}$. Three results stand out. First, participants' choices reveal a preference for electric buses over diesel buses already in the baseline interview—before the enumerator asked any environment-related question and, for treated participants, showed any video. The implied WTP is 21 US cents per ride ($-\beta_{10}^{baseline}/\beta_{20} = .435/.021$). Second, repeated exposure to questions on environmental attitudes and bus-type satisfaction increases the electric-bus preference even for participants in the non-video group: the point estimate for WTP either grows by over one-half ($\beta_{10}^{endline}/\beta_{10}^{baseline} = .700/.435$) or even doubles ($\beta_{10}^{online}/\beta_{10}^{baseline} = .923/.435$). Third, the video treatment increases the electric-bus preference further, by 12 to 13 US cents/ride in the online ($-\beta_{11}^{online}/\beta_{20} = .253/.021$) and endline ($-\beta_{11}^{endline}/\beta_{20} = .265/.021$) encounters. These treatment effects are about one-tenth of the average bus fare in ridership data.[18]

Columns 3-4 introduce random coefficients, which improve model fit (likelihood ratio test, χ^2-statistic $= 1548$, with 9 degrees of freedom) and indicate substantial heterogeneity in preferences for electric buses. The share of participants who prefer electric to diesel buses already at baseline is $\Phi(.585/.789) = 77\%$ (Table 2, first row, mean effect and first row, standard deviation), increasing by endline to 84% in the non-video group and 90% in the video treatment.

Beyond preferences over electric buses, Table 2 indicates that time spent walking to the bus stop carries a larger disutility than riding the bus while seated (Figure 2). This may reflect Singapore's year-round hot and humid climate, which makes walking less pleasant than an air-conditioned bus ride. The implied values of walk time and ride time are 8.2 and 4.5 US$/hour, respectively, equal to 49% and 27% of a median wage rate of 16.8 US$/hour (MRSD, 2022; MOM, 2021).[19] These disamenities are similar to those reported by Hess et al. (2017), of 7.1 and 5.2 US$/hour. The alternative-by-task effects indicate a preference for regular buses in the value-of-time tasks, where they always appear in the left column, but no analogous left-column preference in the bus-type-time tasks, where bus type and other trip attributes vary randomly and may be identical across columns.

As discussed, identification of system 7 assumes that each participant's distaste for

[18] Table A12 reports an average trip distance of 8.2 km, implying a fare of SG$1.41 (US$1.04) (SimplyGo, 2024; PTC, 2024).

[19] Taking the multinomial logit estimates for simplicity, walk time is valued as $.287/.021 \times 60/100 = 8.2$ US$/hour; random-coefficients logit estimates yield similar time values.

in-vehicle ride time is constant within a round across the bus-type-time and the value-of-time tasks. We assess this by estimating the model separately by task type and round. A likelihood ratio test comparing the summed log-likelihoods of the separate models with that of the joint model yields a p-value of 0.98 (Swait and Louviere, 1993), indicating that differences in ride-time coefficients reflect scale factors.[20]

Figure 5 plots median WTP across participants and random draws, calculated using equation 8 (random-coefficients logit; Figure A5's bottom panel shows similar treatment effects with the multinomial logit). At baseline prior to any intervention, median WTP for bus electrification is a significant 20 US cents/ride. In the online and endline rounds, median WTP is reported separately for the video and non-video groups. During the online rounds, both groups exhibit significantly higher WTP than at baseline, with the video group's WTP exceeding that of the non-video group by 15 US cents; this treatment effect is significant at the 5% level (Table A7). These pro-electric shifts in preferences from repeated encounters and the video treatment persist through the endline round. At endline, the video group's WTP is 11 US cents higher than that of the non-video group, and the difference is significant at the 10% level (Table A7).

Extrapolating the campaign's 11 US cent effect on WTP for electric bus rides to Singapore's 1.4 billion annual public bus rides yields an annualized WTP of US$154 million. Dividing this amount by 5,500 diesel buses gives an annual valuation of US$28,000 on replacing each diesel bus fleet with electric. Over a (conservative) 12-year vehicle lifetime and discounted at 3%, repeated communication of the co-benefits of bus electrification increases citizen value by US$1.5 billion. This back-of-the-envelope calculation suggests that preferences for green investment are not a fixed parameter of the policy problem, but can be shifted by communicating the amenities that citizens experience in everyday life.

Appendix A.5 presents sensitivity analyses over alternative samples (e.g., unbalanced versus balanced panel of participants) and specifications (variance structure), reported in Tables A8 and A9 and Figure A5.

[20] The scale-factor estimates in columns 1-2, where $\hat{\kappa}^r < 1$, indicate greater error variance in the value-of-time task than in the bus-type-time task. However, scale factors in this multinomial logit model absorb all random variation, including preference heterogeneity (Brownstone et al., 2000). Once individual heterogeneity is incorporated, in columns 3-4, the baseline scale factor becomes significantly greater than one, while the scale factors in the other two rounds are not significantly different from one.

4.3 Heterogeneity of WTP for electric bus rides

Following Train (2009), we calculate participant-level WTP for electric bus rides at each round (Appendix A.4). Figure 6 shows that from baseline to the online rounds, WTP distributions in both the non-video and video groups shift rightward, with the video group exhibiting higher WTP. By the endline, the distributions appear more dispersed, reflecting substantial heterogeneity from both observed and unobserved characteristics.

Figure A6 again applies the Sorted Effects approach. Mirroring Figure A3's electric-bus satisfaction results, the top panel shows the video treatment increases WTP for nearly all participants: even at the 6th percentile of the distribution, the estimated effect is 7 US cents/ride. The treatment effect has an interquartile range of 9 cents and is convex over percentiles, with pronounced gains in the upper quartile. Based on a regression of conditional mean WTP on video treatment status and its interaction with participant characteristics (as in equation 3), the bottom panels of Figure A6 identify the characteristics of those most and least affected. The findings complement Section 3.3, where treatment was more effective in updating beliefs of participants served by electric buses at their doorstep. Here too, this subgroup exhibits a large WTP increase—underscoring the complementarity between direct experience and information provision in shifting citizen valuation of clean production. Car owners, whose satisfaction regarding electric buses' reduced CO_2 emissions and fumes shifted markedly, also associate with a large WTP increase, as do those with high WTP at baseline.

5 Effects on actual public-transport ridership

Having shown that the video treatment shifted stated preferences—satisfaction with and WTP for cleaner bus technology—we now use the linked farecard data to test whether it also shifted revealed preferences for electric buses (List, 2001; Carson et al., 2014).

5.1 Empirical strategy

We aggregate public-transport ridership for participants who provided farecard numbers at baseline ($N = 580$ with travel in more than one week; Appendix A.6) to the participant-by-week level. We estimate the difference-in-differences (DiD) regression:

$$Y_{it} = \gamma T_i \times Post_{it} + \alpha_i + \alpha_t + \epsilon_{it} \tag{9}$$

where i indexes participants and t indexes week-of-sample 1,2,...,104 in the 2-year data (April 2020-March 2022). The outcome of interest is the probability of taking electric buses. T_i denotes video treatment as before, and $Post_{it}$ equals 1 for all weeks after participant i's baseline interview in September/October 2021. The coefficient γ measures the average treatment effect on the treated (ATT). Participant fixed effects α_i absorb time-invariant differences in characteristics, including travel frequency and mode composition. Week fixed effects α_t control for seasonal patterns, holidays, weather, and other time-varying influences on ridership.

Whether the ATT is short-lived or persistent matters for policy, so we implement the event-study specification:

$$Y_{it} = \sum_{w \neq -1} \gamma_w T_i \times \mathbf{1}(t - BW_i = w) + \alpha_i + \alpha_t + \epsilon_{it} \tag{10}$$

where $\mathbf{1}(t - BW_i = w)$ equals 1 if week t is w weeks relative to the week of participant i's baseline BW_i, i.e., the cohort (Sun and Abraham, 2021). Baseline interviews spanned seven cohorts started in late September 2021.

Bus service 944 is a local feeder linking residential blocks to Bukit Batok town centre, which hosts commerce and the bus and train interchange for onward journeys (Figure A1). Figure A7 shows that the 944 had a high electrification rate, between 50 and 80%, except in May-July 2021, when electric buses were temporarily redeployed elsewhere. We restrict the pre-treatment window to eight weeks before baseline interviews started so that the earliest pre-treatment week does not overlap with this redeployment period.

Because of the staggered baseline rollout, treatment-effect heterogeneity can bias two-way fixed effects estimates (Goodman-Bacon, 2021). We therefore implement the DiD estimator of Callaway and Sant'Anna (2021), comparing the evolution of outcomes between each cohort and the non-video group. The never-treated units form a suitable comparison group because they constitute a sizable share of riders in any given week, and assignment to the video and non-video groups was randomized with equal probability.

Identification relies on the parallel-trends assumption: absent the educational videos, the probability of taking electric buses would have evolved similarly in both groups. Despite the randomized design, we follow Borusyak et al. (2024) to test for violations. We regress the outcome on pre-treatment event-time indicators (up to eight weeks before baseline), controlling for participant and time fixed effects, and test the joint significance of the event-time coefficients. Figure 7 shows no evidence of differential pre-trends in

electric-bus ridership, and the pre-treatment coefficients are jointly insignificant.

5.2 Video treatment effects on actual electric-bus ridership

The top panels of Figure 7 plot trends in the raw data (3-week moving averages) regarding use of electric buses, by video treatment status. Before the intervention, the video and non-video group followed parallel trends. During the intervention, the video group's ridership of the highly electrified bus service 944 grew by one-third over the 3-month campaign to December 2021—and remained elevated until March 2022, when our farecard records end. In contrast, ridership of service 944 in the non-video group fell during and after the campaign.

The bottom panels of Figure 7 show event-study estimates of the video treatment effect on the probability of riding electric buses, and on the probability of riding service 944 specifically. The treatment did not produce an immediate increase in ridership on either electric buses or the 944. Instead, the effect accumulated gradually, reaching a local maximum roughly eight weeks after the baseline interview, and persisted beyond the campaign period up to at least 24 weeks after baseline. Averaged over the post-baseline period, the video treatment increased the probability of riding electric buses by 5.7 percentage points (60% of the pre-baseline mean) and of riding service 944 by 4.9 percentage points (40% of its pre-baseline mean). Table A14 shows that our effect sizes fall within the range of treatment effects estimated in information-intervention studies promoting cleaner mobility—only one of which assesses persistence over months, as we do.

Appendix A.7 presents sensitivity analysis, including a continuous DiD estimator (Callaway et al., 2025) exploiting variation in minutes of video-education exposure among treated participants, some of whom skipped rounds and therefore video clips.

Mechanisms. Figure A8 suggests that the video treatment had a negligible impact on overall public-transport usage—whether measured by trip frequency, duration, or distance. Comparing self-reported travel in the week before the endline to that before the baseline, we find no evidence of substitution across travel modes either (Figure A9).

We next test whether participants substituted into electrified bus services. Here we focus on trips with at least one segment starting and arriving within 1,500m of bus 944 stops; these trips account for 52% of all trips in the farecard data. We then calculate the share of trips containing at least one electric-bus segment. Figure A10, panel a shows that the treatment raised this electric-bus trip share by 2 percentage points (50% over the pre-baseline

mean), suggesting that treated participants not only began using electric buses but actively re-optimized their routes to incorporate them. Disaggregating by single-segment rides versus trips integrating electric buses with other bus or train services (roughly 30% of all trips), we find the increase is driven primarily by multisegment trips connecting electric buses, especially service 944, for onward journeys (Figures A1 and A10, panels b-d).

High-frequency route choices in a dense network offering multiple reasonable paths to a destination—visible in a standard travel planner such as Google Maps (and at baseline 75% of public-bus commuters reported using such a phone app)—uniquely allow us to observe citizens actively re-optimizing their routes in favor of cleaner technology. Analogous to the forced experimentation in Larcom et al. (2017), where a transit disruption led commuters to discover and persist with better routes, the shift in appreciation (Figures 3 and A3) and valuation (Figures 5 and 6) induced by the video treatment triggered voluntary experimentation with electric buses that outlasted the campaign's end in December 2021, persisting through March 2022 when our observation window closed (Figure 7).

5.3 Heterogeneous shifts in electric-bus use

We examine heterogeneous treatment effects via subsample analysis, as is standard in nonparametric estimation (Callaway and Sant'Anna, 2021). Experimentation with unfamiliar services or technology may be less costly outside peak hours (Kreindler, 2024) (peak hours = 35% of trips; Table A12). Figures 8 (row 1) and A15 suggest somewhat larger effects during off-peak hours, though differences are not significant.

Figure 8 (row 2) shows that treatment is more effective when the highly electrified service 944 stops at a participant's doorstep—the red versus blue housing blocks in Figure A1 (balanced in number; Table A10). Treatment is effective among participants without a household car but not among car-owners (Figure 8, row 3), who account for one-quarter of the active farecard subsample (Table A10). Figure A16 disaggregates by the four subgroups defined by the intersection of car ownership and residential proximity; treatment is most effective for non-car-owning participants living near the 944. Results are similar using self-reported car usage or public transport usage at baseline (Figure 8, row 4 and 5; figures analogous to A16 omitted).

These results are consistent with the value of convenience: the video treatment increased the electric-bus preference by under one minute of walk time on average—$\beta_{11}^{endline} < \beta_{40}$ in Table 2—yet participants in blocks further from service 944 must walk more than one

minute to reach its stops (Figure A1). Moreover, Section 4 measured preferences across bus types, not substitution away from car travel, which car owners might find most convenient for trips they already take by car. Given the robust behavioral response among non-car owners and residents near electrified services, our results underscore the value of educational campaigns as urban bus services are electrified worldwide.

The remainder of Figure 8 explores differential treatment effects along other demographic dimensions, such as the presence of young children in the household and participant age, given that travel-schedule flexibility may vary over the lifecycle.

6 Effects on general-domain environment attitudes

Previous sections show that the video treatment shifts both stated and revealed preferences for electric buses. We now ask whether this campaign-induced shift extends beyond the public-transport domain to general environmental attitudes and policy support.

We estimate equation 3 on the summary index of environmental attitudes measured at baseline and endline (Figure 1), allowing the treatment effect to vary by residential proximity to the highly electrified service 944. The video treatment does not significantly shift attitudes in the full sample, but it does among participants living close to service 944 stops (top panel of Figure 9). The bottom panel of Figure 9 shows that the effect on the attitudes composite is strongest among participants with moderate baseline environmental awareness, between the 60th and 80th percentiles of the distribution. This pattern is consistent with persuasion models in which attitude change is most likely among marginal individuals rather than those at the extremes (DellaVigna and Gentzkow, 2010).

The 13 statements collectively spanned environmental stewardship, climate anxiety, intergenerational equity, public policy, and the role of individual action. Estimating the treatment effect for each statement separately, we find a significant shift in agreement that road vehicles, including public buses, are a major source of PM2.5 (Figure A18, row 1). The repeated comparison of electric and diesel buses during the campaign appears to have heightened awareness of road-transport air pollution among participants with direct experience of the cleaner technology.

This heightened awareness accompanies behavioral change. Figure A17 divides participants into four subgroups by baseline-to-endline change in the environmental attitudes index and residential proximity to service 944 stops. The video treatment produces the largest increase in electric-bus ridership among participants whose attitudes improved

the most and who live near service 944. These results point to the complementary roles of domain-specific information provision and direct experience in shifting environmental attitudes beyond the specific technology domain in which cleaner production is introduced.

7 Discussion

This paper asks whether governments that invest in green infrastructure can build public support by emphatically communicating the benefits of that investment to citizens.[21] We study this in the context of urban bus electrification, using a three-month RCT with 1,200 households that combines experience with the clean technology, repeated education, stated-preference elicitation, and two years of farecard-linked public bus and train ridership data.

The answer is yes, and the mechanism matters. Repeated communication of both private and social co-benefits—not a one-off nudge—shifts satisfaction, willingness to pay, and actual commuting behavior toward cleaner bus technology, with effects that build gradually and persist beyond the campaign. The strongest responses emerge among participants who live near electrified bus services, suggesting that information provision and direct experience are complements rather than substitutes. Among car owners, the videos shift stated preferences but not behavior—a divergence that underscores the importance of jointly examining stated and revealed preferences when evaluating the effectiveness of public policy, and that highlights the real-world switching costs faced by marginal adopters (for example, car owners for whom expressing pro-social intentions is personally less costly than actually reducing their car use).

Several aspects of our evidence bear emphasis. We track the same participants over seven encounters spanning several months, observing how preferences respond to sustained exposure rather than to a single informational shock, mimicking how a concerted effort to educate citizens might be scaled. The panel data reveal that preferences are not fixed (complicating welfare analysis built on stable preferences; Mattauch et al. (2022); Carattini et al. (2024)): they shift with education, and the shift is amplified by direct experience of the cleaner technology. These stated-preference shifts are borne out in farecard records, where treated participants persistently increase their use of electric buses well after the campaign ends. The combination of repeated engagement, preference malleability,

[21] While one of the coauthors was the government transit agency's chief economist of planning at the time of the study, the research was academic and was communicated to participants as such (see links to research instruments on the cover page).

the link from stated to revealed preferences, and evidence of persistence is, to our knowledge, novel in this literature.

Another consequential finding is that educating citizens about one green infrastructure investment—in public transport—shifts general environmental attitudes beyond that domain. The effect is strongest among participants with direct experience of the cleaner technology and those in the middle of the attitude distribution, consistent with persuasion operating on the marginal citizen rather than at the extremes. This cross-domain spillover matters because accelerating the green transition requires not only technological progress but also broad public understanding and support. Education in one specific domain may generate the wider attitudinal shifts needed to sustain political demand for decarbonization across the economy. Future research can assess whether communicating the co-benefits of other green investments—in energy, food, or housing and urban form[22]—generates similar cross-domain spillovers.

Our setting has limitations. Singapore's dense, integrated transit network with distance-based fares (which do not penalize the number of bus and train rides within a single trip) facilitate modal substitution. This response may not transfer directly to car-dependent cities with limited transit alternatives—though we argue that for our study this is a strength by allowing us to observe individuals voting with their feet. The electrified bus service we study is a short-distance feeder route; whether similar effects arise on longer-distance services remains an open question. And our stated WTP estimates are likely inflated by hypothetical bias and the focused attention of an experimental setting, though since this bias affects both video and non-video groups symmetrically, the treatment effect of 11 US cents per ride—or $1.5 billion across the lifetime of a fleet of 5,500 electric buses—is robust to this concern.

These caveats point to a broader research agenda. Future work could test whether sustained and scalable co-benefit communication remains effective in car-dependent cities and whether richer experimental designs incorporating bias-mitigation techniques (e.g., using cheap talk or opt-out reminders (Börger et al., 2025; Chopra and Vossler, 2026)) yield more conservative but still economically meaningful WTP shifts. More broadly, our findings suggest that targeted, credible communication on how green infrastructure tangibly benefits citizens in one domain of their daily lives may shift support for policies that hasten the plural, less visible low-carbon transitions.

[22]Co-benefits may include energy affordability, energy security, green jobs, air quality, social justice, active mobility, biodiversity, food security, nutrition and health, zoonotic disease risk, antibiotic resistance, and more.

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Tables

Table 1: Average treatment effects on electric-bus satisfaction

Dependent variable:	Electric-bus satisfaction versus diesel buses						
	Less CO_2 emissions	Less climate change	Less fumes	Quieter travel	More reliable service	Better for the environment	Satisfaction summary index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Electric-bus satisfaction relative to diesel bus (5-point scale, Strongly (Dis)Agree = (-2) 2, randomized order)							
Video treatment	0.23***	0.23***	0.18***	0.22***	0.21***	0.19***	0.20***
	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.03)
Mean at baseline, t_1	1.03	0.98	1.13	1.04	0.38	1.05	0.05
Std. dev. at baseline	1.27	1.28	1.30	1.27	1.17	1.29	0.97
B. Agree/Strongly Agree that electric bus outperforms diesel bus (yes = 1, randomized order)							
Video treatment	0.07***	0.06***	0.05***	0.08***	0.09***	0.05***	
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	
Mean at baseline, t_1	0.70	0.69	0.75	0.70	0.37	0.72	
Std. dev. at baseline	0.46	0.46	0.43	0.46	0.48	0.45	
Number of participants	1097	1097	1097	1097	1097	1097	1097
Number of observations	2738	2738	2738	2738	2738	2738	2738

Notes: OLS estimates of equation 1. An observation is a participant-encounter pair (post-baseline encounter). The estimation sample includes 1,097 participants who completed at least one post-baseline encounter in which electric-bus satisfaction was elicited (Figure 1). In Panel A, the dependent variable is electric-bus satisfaction relative to diesel buses, measured on a 5-point Likert scale, for the co-benefit dimension indicated in column 1 to 6: reduced carbon emissions, climate mitigation, less fumes, quieter travel, service reliability, and environmental impact; column 7 examines a satisfaction summary index (Anderson, 2008). In panel B, the dependent variable is an indicator equal to one if the participant Agrees or Strongly Agrees that electric buses outperform diesel buses. Controls include satisfaction with the dimension at baseline, the comparison order between electric and diesel buses and its interaction with an online-round indicator, and fixed effects for calendar date and start hour. Standard errors are clustered at the participant level. Significant at *10%, **5%, and ***1%. Table A6 shows that results are robust in a balanced sample of 716 participants who completed all encounters in which electric-bus satisfaction was elicited.

Table 2: Structural model estimates from the choice experiments over time

	Multinomial logit model		Random-coefficients logit model	
	Estimate (1)	S.E. (2)	Estimate (3)	S.E. (4)
Mean effects (β)				
Electric bus, baseline ($\beta_{10}^{baseline}$)	0.435***	(0.060)	0.585***	(0.084)
Electric bus, online (β_{10}^{online})	0.923***	(0.092)	0.977***	(0.125)
Electric bus, endline ($\beta_{10}^{endline}$)	0.700***	(0.085)	0.983***	(0.143)
Electric bus, online × Video T (β_{11}^{online})	0.253**	(0.114)	0.356***	(0.135)
Electric bus, endline × Video T ($\beta_{11}^{endline}$)	0.265**	(0.109)	0.292*	(0.155)
Fare (β_{20})	-0.021***	(0.001)	-0.032***	(0.004)
Ride time, baseline ($\beta_{30}^{baseline}$)	-0.159***	(0.011)	-0.236***	(0.040)
Ride time, online (β_{30}^{online})	-0.173***	(0.011)	-0.190***	(0.031)
Ride time, endline ($\beta_{30}^{endline}$)	-0.142***	(0.010)	-0.201***	(0.052)
Walk time (β_{40})	-0.287***	(0.013)	-0.499***	(0.059)
Std. deviations and correlation (Σ_{β})				
Std.dev. electric bus, baseline			0.789***	(0.234)
Std.dev. electric bus, online			0.481**	(0.205)
Std.dev. electric bus, endline			1.008***	(0.176)
Std.dev. fare			0.027***	(0.004)
Std.dev. ride time, baseline			0.201***	(0.029)
Std.dev. ride time, online			0.083***	(0.029)
Std.dev. ride time, endline			0.170**	(0.069)
Std.dev. walk time			0.513***	(0.069)
Corr., walk time & ride time, baseline			0.213*	(0.110)
Corr., walk time & ride time, online			0.417***	(0.143)
Corr., walk time & ride time, endline			0.215**	(0.087)
Alternative-by-task effects (δ)				
$\delta_A^{BT,baseline}$ (left bias)	-0.090*	(0.048)	-0.113*	(0.059)
$\delta_A^{BT,online}$ (left bias)	0.039	(0.041)	0.055	(0.047)
$\delta_A^{BT,endline}$ (left bias)	0.014	(0.042)	0.055	(0.052)
$\delta_A^{VOT,baseline}$ (pref. regular bus)	0.766***	(0.157)	0.490***	(0.080)
$\delta_A^{VOT,online}$ (pref. regular bus)	0.681***	(0.079)	0.533***	(0.084)
$\delta_A^{VOT,endline}$ (pref. regular bus)	0.512***	(0.136)	0.280***	(0.082)
Scale factors (κ, ζ^{BT})				
$\kappa^{baseline} = \zeta^{VOT,baseline}/\zeta^{BT,baseline}$	0.574***	(0.094)	2.202***	(0.285)
$\kappa^{online} = \zeta^{VOT,online}/\zeta^{BT,online}$	0.762***	(0.069)	0.923	(0.120)
$\kappa^{endline} = \zeta^{VOT,endline}/\zeta^{BT,endline}$	0.491***	(0.077)	1.118	(0.173)
$\zeta^{BT,online}$	1.628***	(0.108)	1.892***	(0.229)
$\zeta^{BT,endline}$	1.381***	(0.092)	1.705**	(0.214)
Number of participants	1200		1200	
Number of observations	13,930		13,930	
Log-likelihood	-7818.7		-7044.6	
Adjusted ρ^2	0.188		0.267	
AIC	15,679.4		14,149.3	

Notes: Estimates from two specifications of equation 5. The estimation sample includes all choice situations from the baseline, online, and endline encounters. *Video T* is an indicator equal to one for participants assigned to the video group. Columns 1-2 report estimates from a multinomial logit model, while columns 3-4 report estimates from a random-coefficients logit model. The coefficients β_2, $\boldsymbol{\beta_3}$, β_4 are assumed to follow log-normal distributions. For ease of interpretation, we report coefficient means and standard deviations in levels rather than the underlying log-scale parameters; standard errors are obtained using the delta method. In the *Scale Factors* panel, $\zeta^{BT,baseline}$ is normalized to 1, so all other scale factors are interpreted relative to this base value, with significance levels corresponding to tests against unity. Standard errors are clustered at the participant level. Significant at *10%, **5%, and ***1%.

Figures

Figure 1: RCT design, implementation, and questions

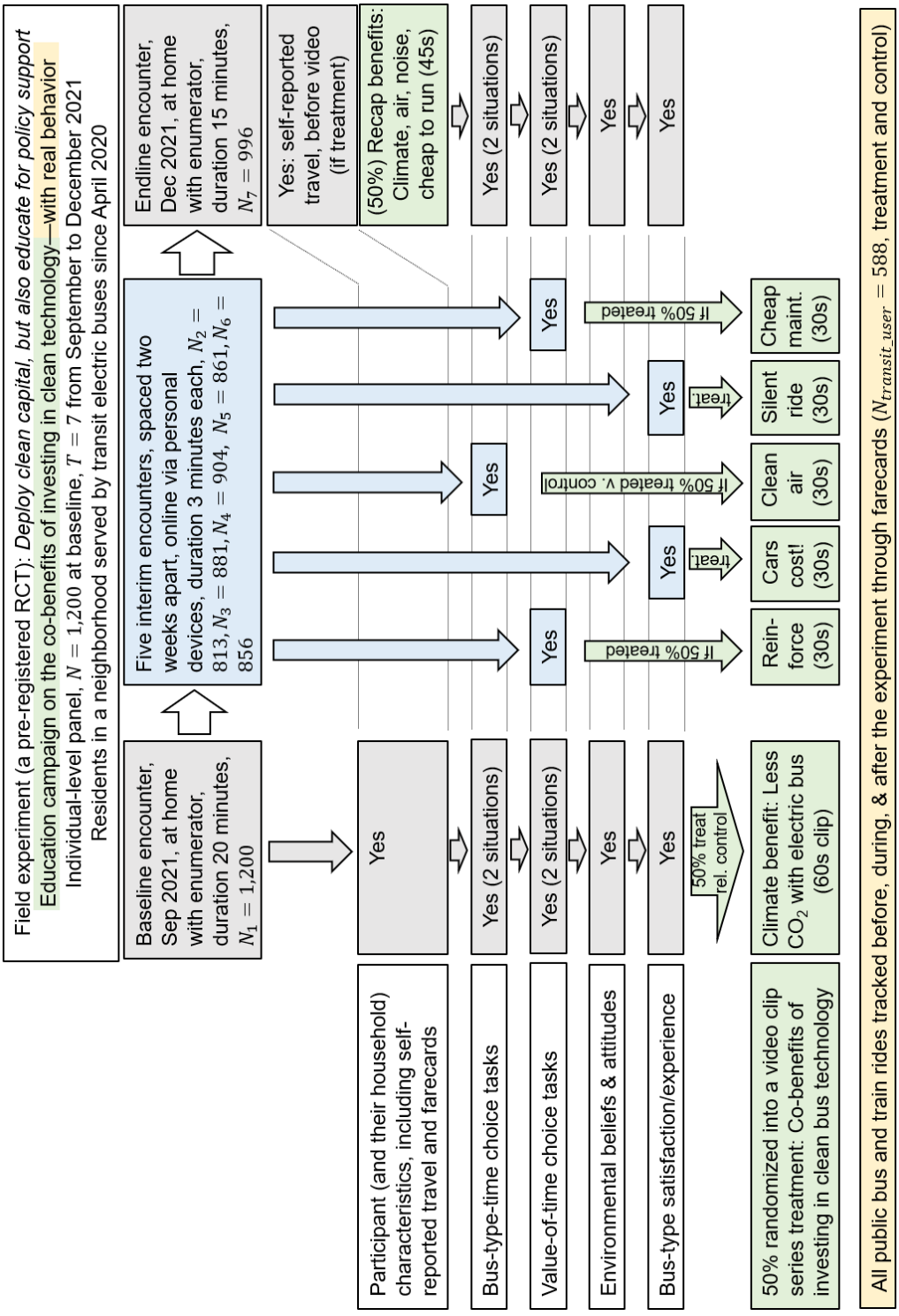


Figure 2: Examples of two types of choice task

	Option A			Option B		
Walk time to the bus stop	1 minute	5 minutes	10 minutes	1 minute	5 minutes	10 minutes
						
Wait time	Similar			Similar		
Bus type	DIESEL 			ELECTRIC 		
Ride time sitting on bus	10 minutes	15 minutes	20 minutes	10 minutes	15 minutes	20 minutes
						
Which option do you prefer?	PREFER THIS OPTION			PREFER THIS OPTION		

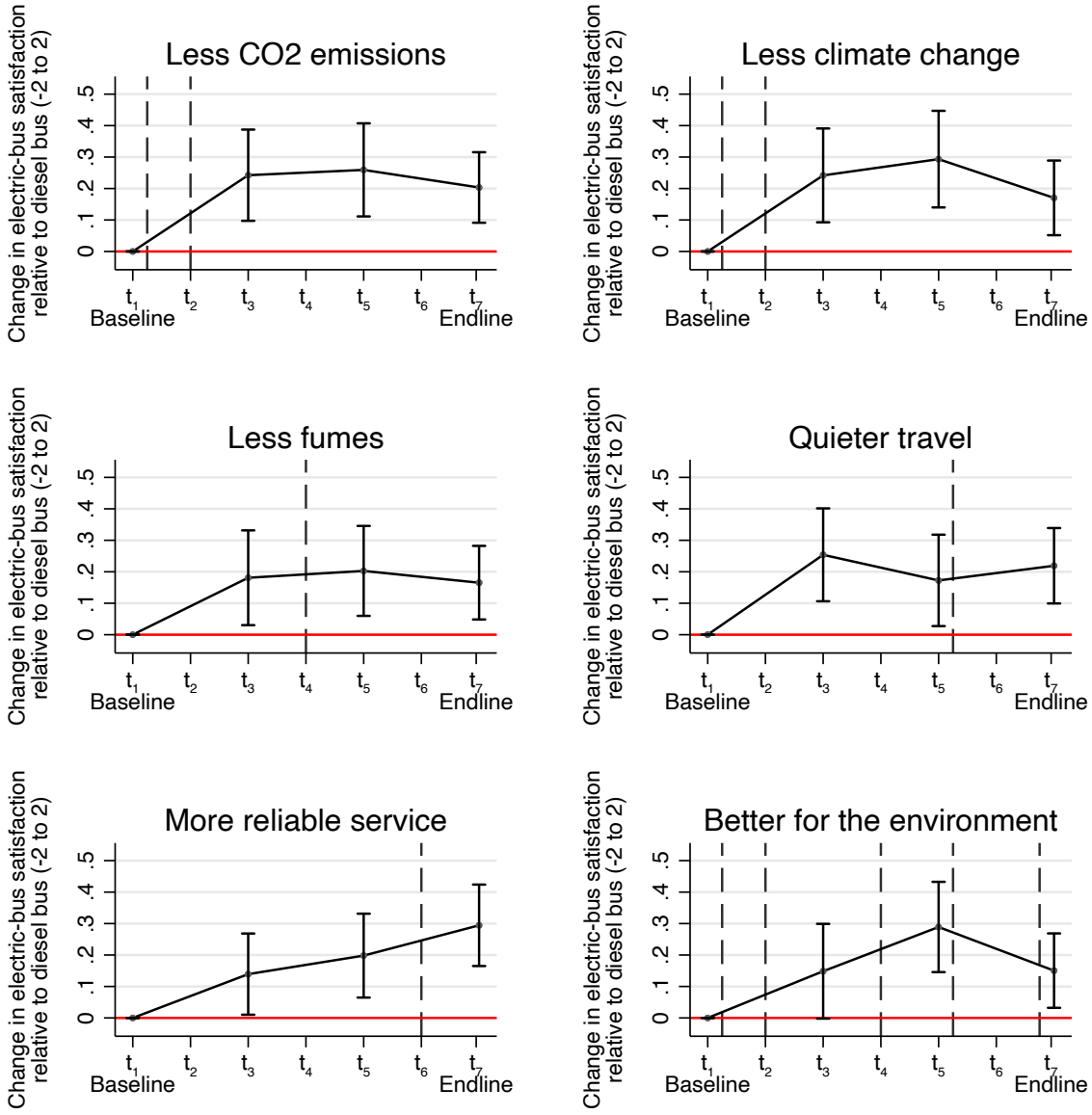
(**a**) Bus-type-time task

	Option REGULAR	Option EXPRESS
Route	Regular	Express
Wait time	Similar	Similar
Ride time sitting on bus	35 minutes	20 minutes
Fare	$1.25	$2.00
Which option do you prefer?	PREFER THIS OPTION	PREFER THIS OPTION

(**b**) Value-of-time task

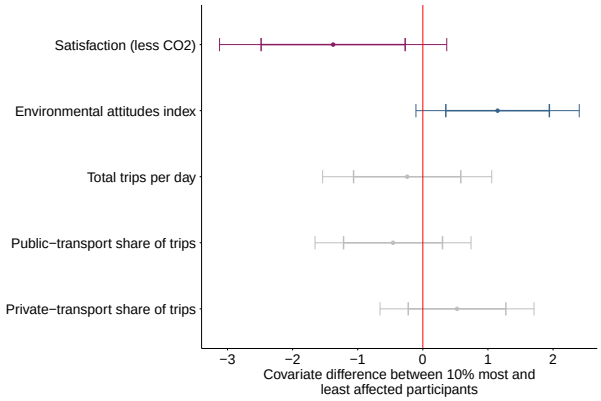
Notes: The top panel shows an example of a bus-type-time choice task. The illustrated attribute values are one of many possible combinations: for example, an electric (resp., diesel) bus could instead appear in alternative A (resp., B), or not appear at all. To reduce cognitive load, most bus-type-time tasks varied two attributes rather than the maximum of three illustrated here. The bottom panel shows an example of a value-of-time choice task. The illustrated attribute values are one draw from the 40 combinations shown in Figure A4. The $ symbol shown to participants denotes SG$ (US$ 1 = SG$ 1.35). For both task types, wait time was fixed as "Similar" across alternatives. Bus cabin seating is a common experience for commuters. Boldface and color highlights are as shown to participants.

Figure 3: Dynamic effects of the video treatment on electric-bus satisfaction

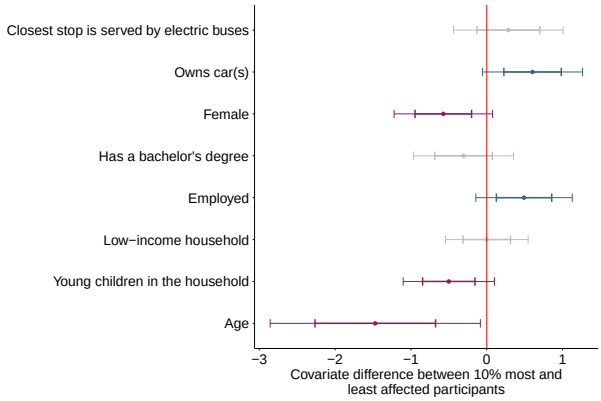


Notes: 95% confidence intervals for dynamic treatment effects (i.e., compared with the non-video group) using equation 2. The dependent variable is electric-bus satisfaction relative to diesel buses, for the co-benefit dimension indicated: reduced carbon emissions, climate mitigation, less fumes, quieter travel, service reliability, and environmental impact. Scores are measured on a 5-point Likert scale and are coded as -2 (Diesel bus is better) through 0 (Same) to 2 (Electric bus is better). The estimation sample includes 1,097 participants who completed at least one post-baseline encounter in which satisfaction was elicited (Figure 1); results with a balanced sample are similar. In the horizontal axis, t_1 denotes the baseline interview, t_2 is the first online round, and so on. Vertical dashed lines mark encounters in which the corresponding topic video was shown to the treatment group. For example, videos comparing carbon emissions from electric and diesel buses were shown at the end of the baseline (and after the bus-type satisfaction question) and at the end of the first online encounter (no satisfaction question), thus vertical dashed lines are added just right of t_1 and of t_2. Other notes in the caption to Table 1 apply here.

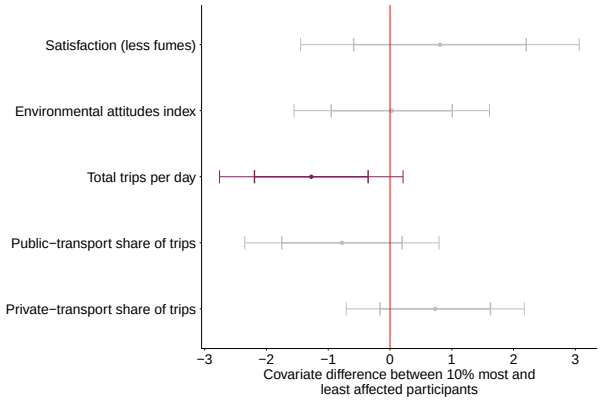
Figure 4: Characteristics of participants whose electric-bus satisfaction is most and least influenced by the video treatment



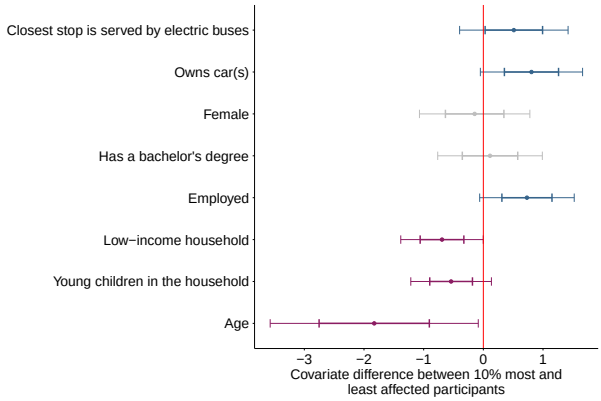
(**a**) Less CO_2 emissions: Baseline outcomes



(**b**) Less CO_2 emissions: Demographics



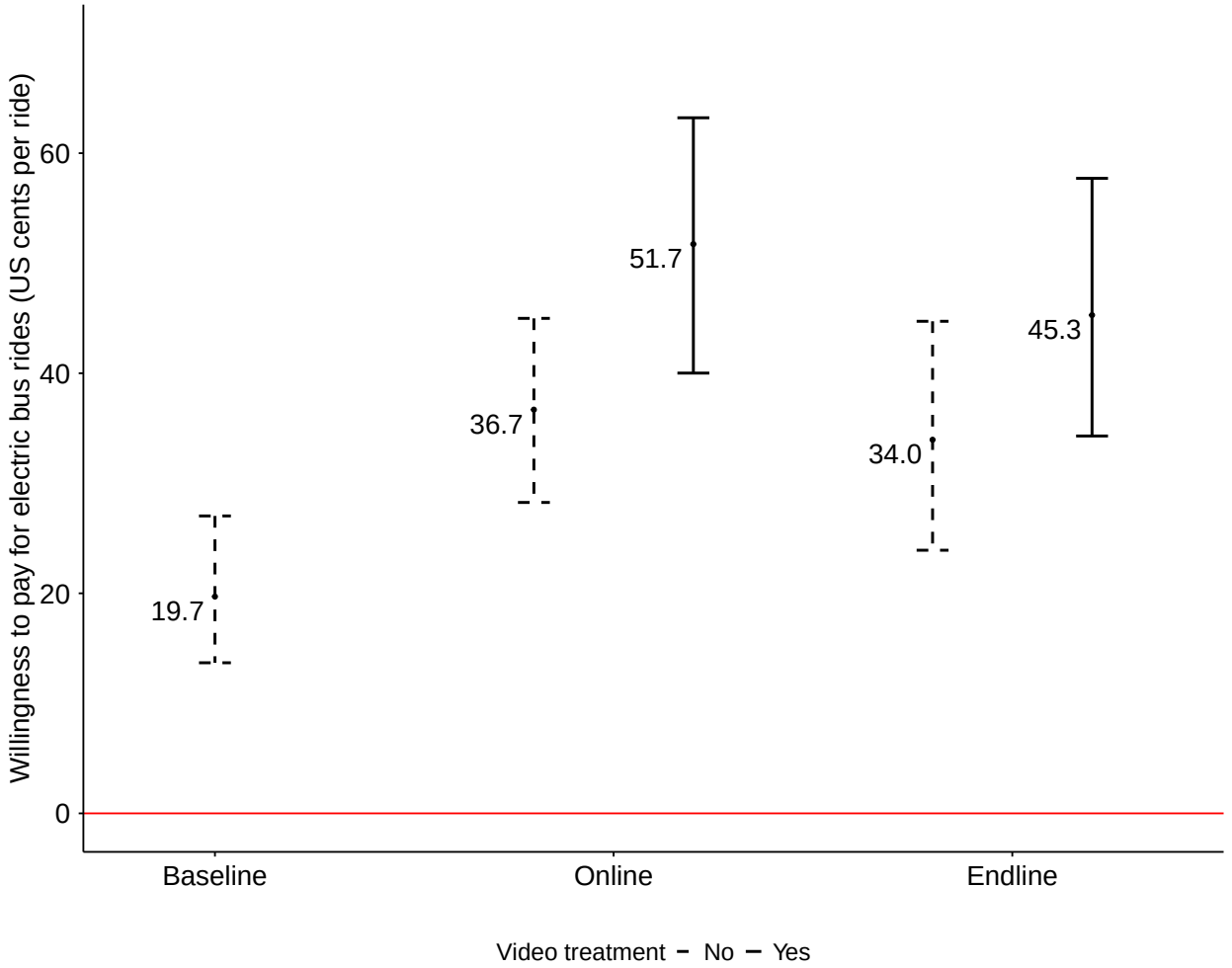
(**c**) Less fumes: Baseline outcomes



(**d**) Less fumes: Demographics

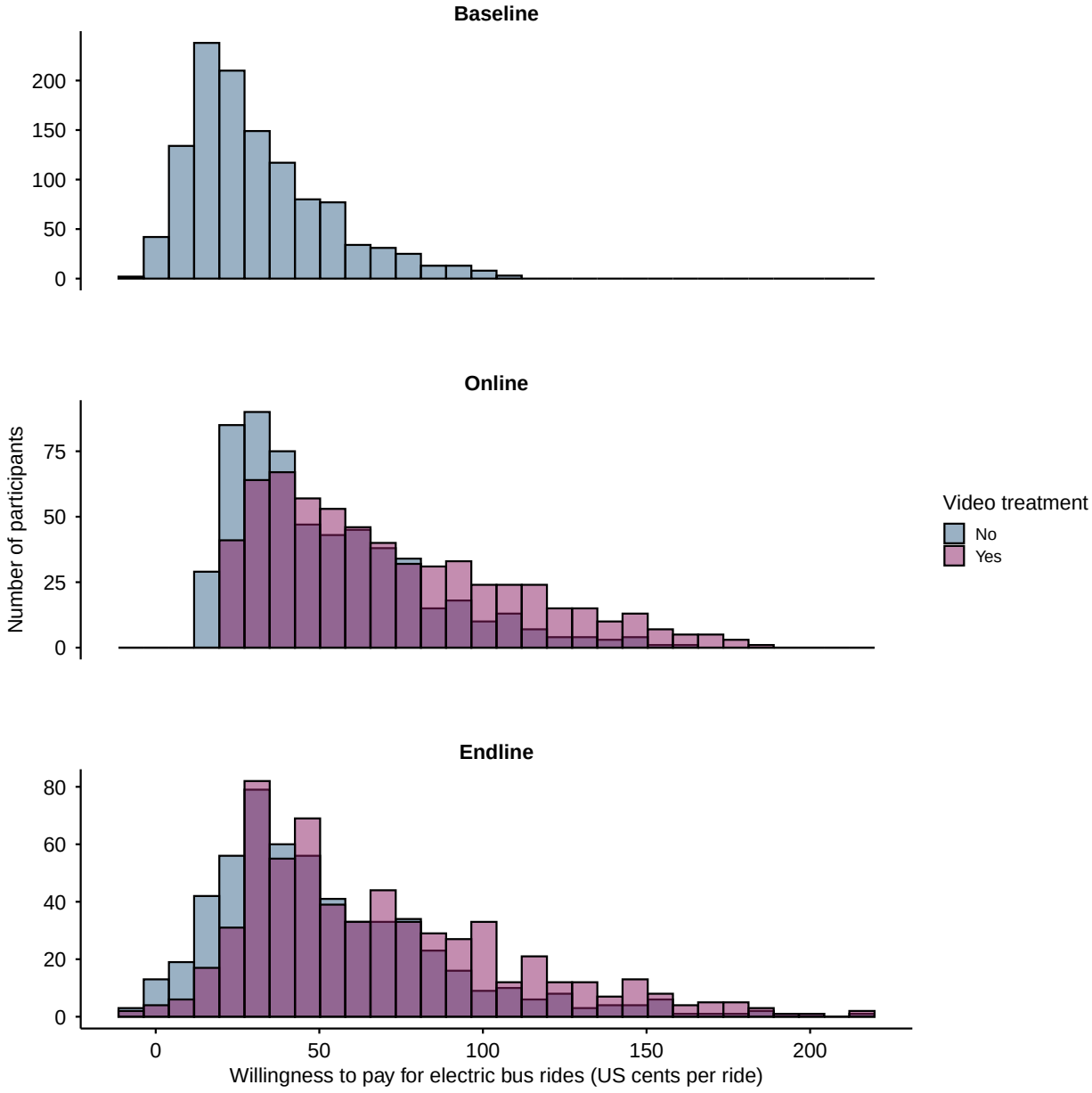
Notes: Covariate differences between the top and bottom deciles of video-treatment effects on electric-bus satisfaction across two co-benefit dimensions that exhibit significant treatment heterogeneity: carbon emissions and fumes. For example, a positive covariate difference for the environmental-attitude index indicates that the video treatment raises electric-bus satisfaction with carbon emissions more for participants who are more pro-environmental at baseline. Covariates are divided into two families: baseline outcomes (left panels) and demographic covariates (right panels). Continuous covariates are standardized using the baseline mean and standard deviation. Dots indicate point estimates. Narrow bars show independent 95% confidence intervals, while wider bars show uniform confidence intervals adjusted for the family-wise error rate within each covariate family. Both sets of intervals are computed from 5,000 bootstrap replications (Chernozhukov et al., 2018). Significant positive (negative) differences at the 5% level are labeled in blue (red), while insignificant differences are labeled in gray.

Figure 5: WTP for electric bus over the campaign by video treatment status



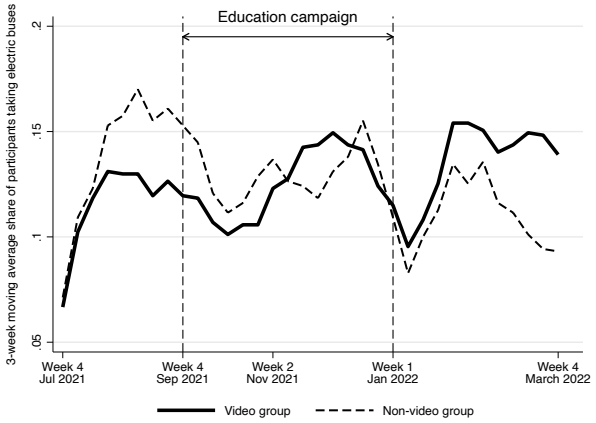
Notes: Median WTP for electric bus rides across participants and random draws, based on the random-coefficients model estimates in Table 2, columns 3-4. Dashed and solid lines correspond to the non-video and video groups, respectively. Dots indicate point estimates, and whiskers denote 95% confidence intervals computed using the Krinsky-Robb method. Table A7 reports the full set of combinatorial tests for differences in WTP across rounds and in non-video vs. video treatment.

Figure 6: Distribution of WTP for electric bus by video treatment status

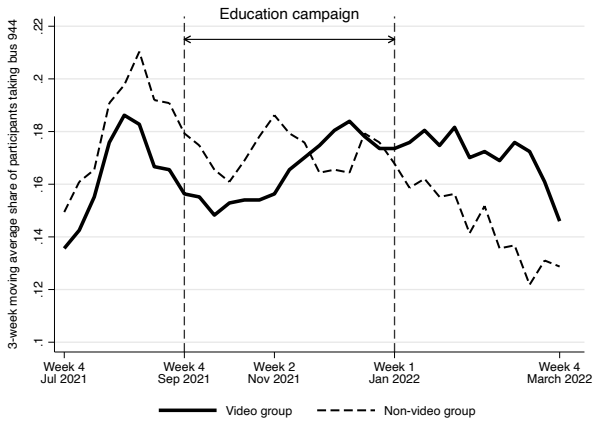


Notes: Conditional mean WTP for electric bus rides across participants (Train, 2009), based on the random-coefficients model estimates in Table 2, columns 3-4. Red bars represent the video group; blue bars the non-video group. Panels correspond, from top to bottom, to the baseline, online, and endline rounds. All participants at baseline are labeled as non-video because treated participants saw the first video only at the end of the baseline interview. Observations above the 99th and below the 1st percentile are excluded for visualization.

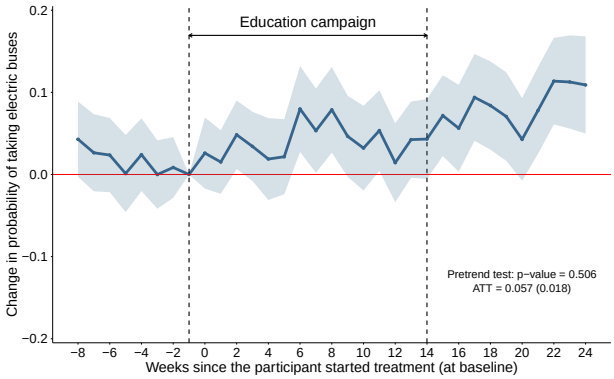
Figure 7: Video treatment effect on the probability of riding electric buses and highly electrified bus service 944



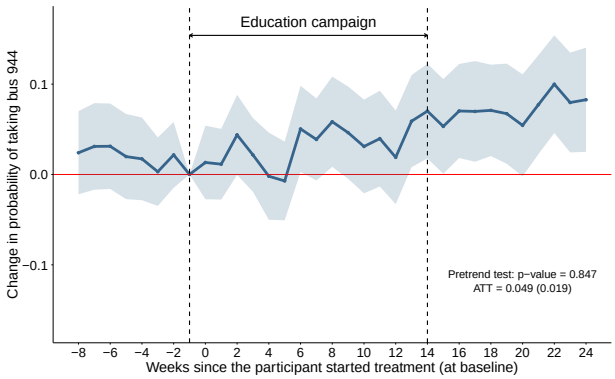
(**a**) Share of participants riding electric buses (any service)



(**b**) Share of participants riding service 944



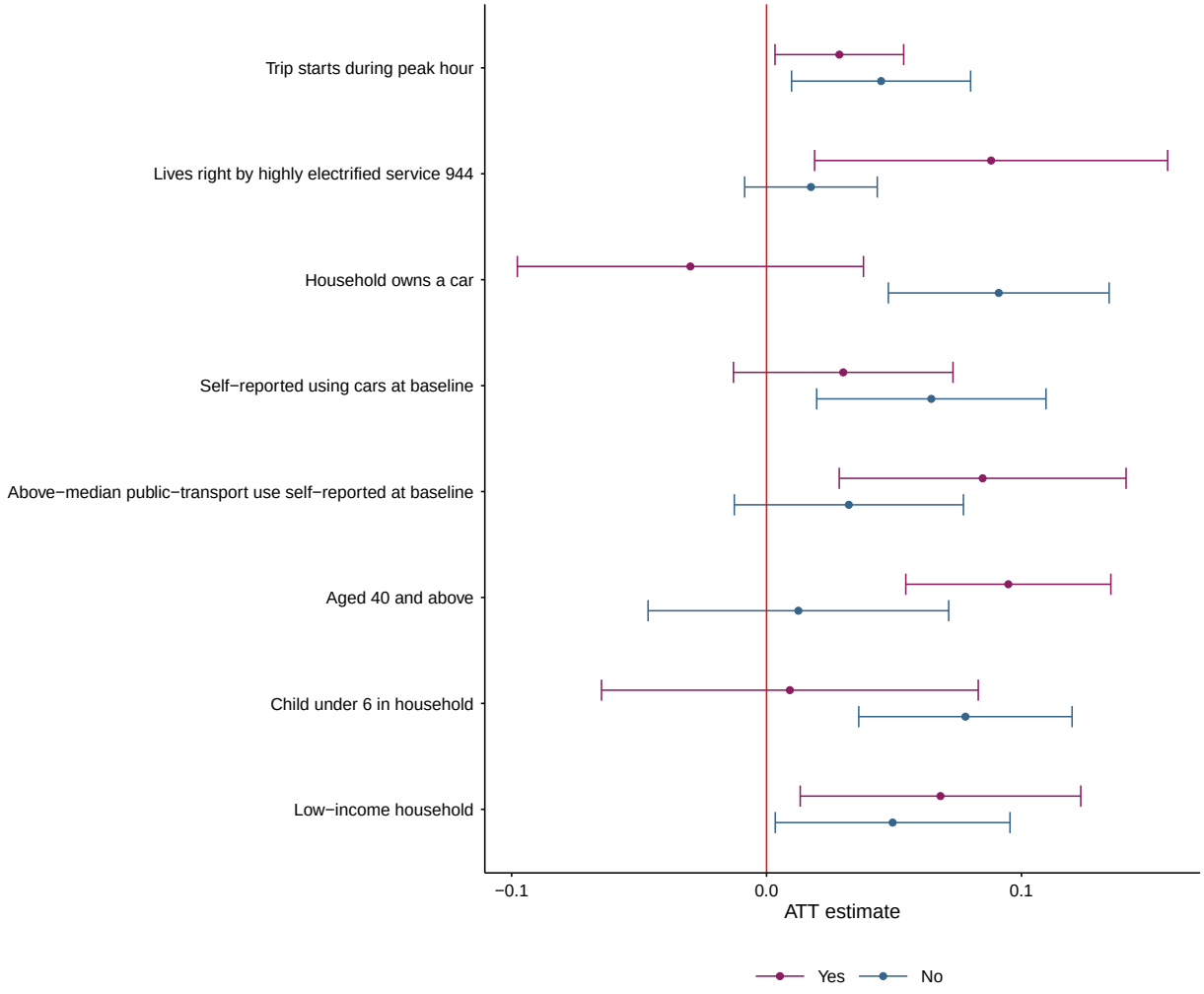
(**c**) Event study: Probability of riding electric buses (any service)



(**d**) Event study: Probability of riding service 944

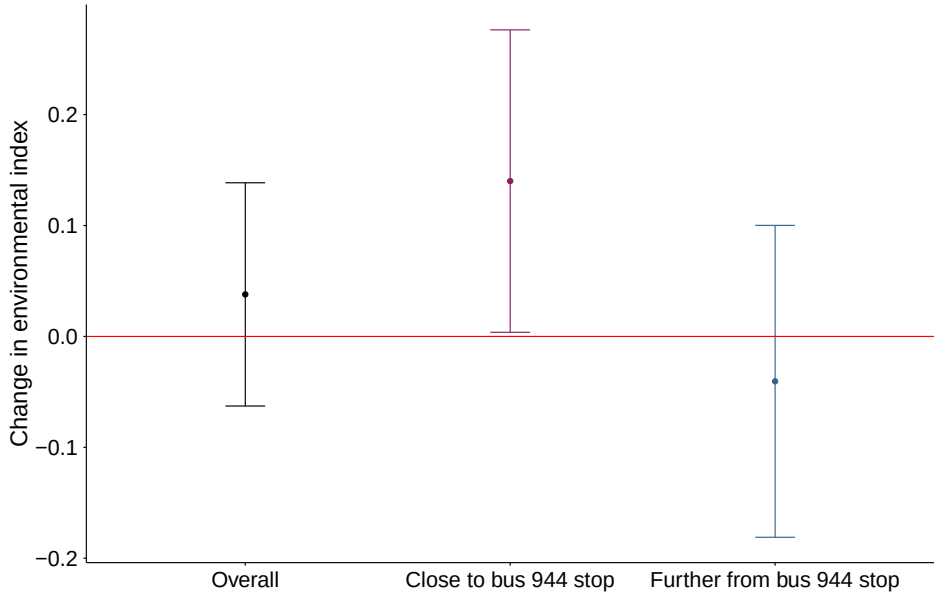
Notes: The top panels show weekly shares of participants riding (a) electric buses (any service) and (b) the highly electrified bus service 944, by video treatment status. Three-week moving averages are plotted before (starting the week of July 30, 2021), during, and after the education campaign. The bottom panels show event study estimates of the video treatment effect on the probability of riding (c) electric buses (any service) and (d) the service 944, using the Callaway and Sant'Anna (2021) estimator. Point estimates and 95% confidence intervals are shown from eight weeks before to 24 weeks after each participant's baseline interview. The bottom panels report pre-trend test p-value (Borusyak et al., 2024) and the ATT estimate. The balanced panel comprises 580 participants over 104 weeks.

Figure 8: Heterogeneous impact of video treatment on the probability of riding electric buses, by trip or participant characteristics

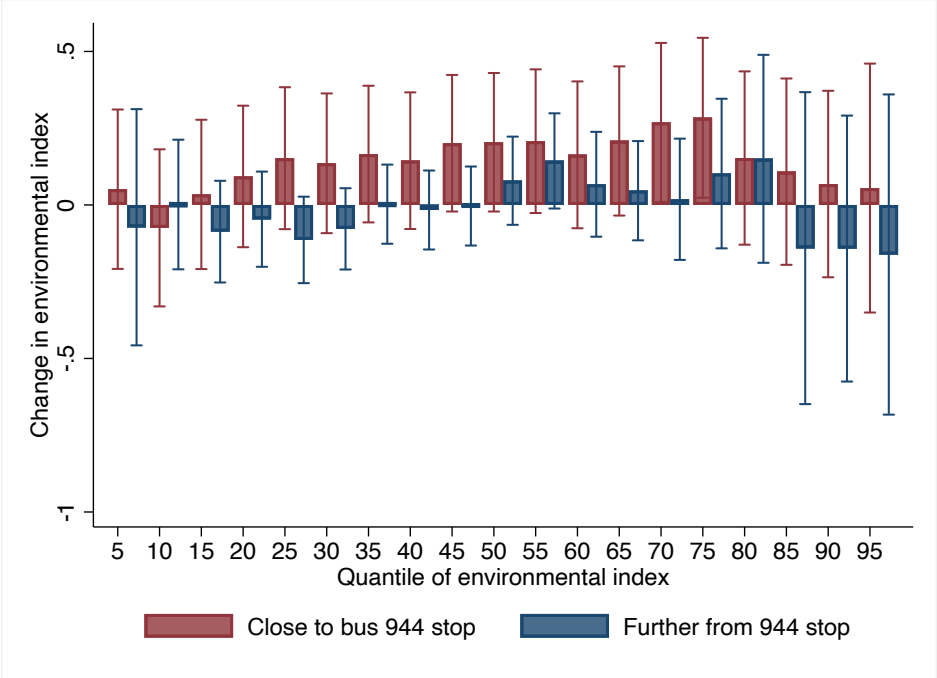


Notes: ATT estimates of the video treatment effect on the probability of riding electric buses (any service), using the Callaway and Sant'Anna (2021) estimator applied separately to the subsamples indicated in each row. Dots are point estimates; whiskers are 95% confidence intervals.

Figure 9: Video treatment effect on general environmental attitudes



(**a**) Average treatment effect



(**b**) Quantile treatment effect

Notes: Video treatment effect on the summary index of environmental attitudes (13 items; Table A3), by distance to electrified bus service 944 stops. To prepare this figure, we use baseline and endline responses for 996 participants who completed both interviews. Panel a shows the average treatment effect on the summary index, using equations 1 (overall) and 3 (interaction of treatment indicator and proximity to service 944 stops). Effects by statement are in Figure A18. Panel b shows the treatment effect at different quantiles of the summary index, estimated separately using unconditional quantile regression (Firpo et al., 2009) for participants living close to and further from service 944 stops. Dots/bars are point estimates; whiskers are 95% confidence intervals.

Online Appendix for "Preference Malleability When Sustained Information and Experience Interact: Evidence from Bus Electrification"

A Supplementary text, tables, and figures

A.1 Self-reported travel patterns

In the baseline and endline interviews, participants answered two questions about their travel patterns. The first measured weekly travel frequency: "In the past week, on how many days did you travel by public bus, MRT, car, motorcycle, or van/lorry?" Participants selected one of eight options ranging from "Less than 1 day a week" to "7 days a week." The second question measured daily trips by mode: "On a typical day in the past week, how many trips did you make by motorized mode of travel?" Modes included public bus, trains, owned cars, taxi/private hire cars, motorcycles, owned vans/lorries, and other modes. For each mode, participants chose from six options: "0 trips a day," ... "4 trips a day," and "5 or more trips a day" (which we code as 5). We define total daily trips as the sum across all modes. We group modes into (1) Public Transit (public buses and trains) and (2) Car Trips (owned cars and taxi/private hire cars). Each mode's trip share is its trips divided by total daily trips.

A.2 Attribute manipulation for the two choice tasks

Bus-type-time choice task. In the baseline, the third online round, and the endline, the participant considered "different imagined scenarios. For each question, please choose truthfully which one scenario you prefer. There are no right or wrong answers. This is a matter of personal preference and your answers are anonymous." Attribute values were drawn independently across the two alternative bus trips and across attributes. Walk time "from your block" to the bus stop (in minutes) was drawn from $(1, 5, 10)$ with equal probability; bus type from $(\text{diesel}, \text{electric})$ with equal probability; and ride time while seated from $(10, 15, 20)$ minutes with equal probability. Denote the draws for alternatives A and B as (walkA, walkB), (busTypeA, busTypeB), and (rideA, rideB), respectively.

We then applied rejection rules to eliminate uninformative combinations:

1. *Identical alternatives*: Drop if all three attributes coincide across A and B.
2. *Large commute difference*: Drop if $|\text{walkA} + \text{rideA} - \text{walkB} - \text{rideB}| \geq 10$ minutes.
3. *Likely dominant alternative*: When busTypeA = busTypeB and one alternative weakly dominates the other on both walk and ride time (with strict dominance on at least one), drop with probability $1/2$; for example, (walkA $>$ walkB, busTypeA = busTypeB, rideA = rideB) would be dropped.

Value-of-time choice task. This task was administered in the baseline, the first and fifth online rounds, and the endline. The question noted that "Express Buses get you to your destination faster because they skip some stops along the way, but they are more expensive." Ride time and fare varied jointly across questions, drawn with equal probability from the 40 combinations in Figure A4. Express-bus fare

premiums started low—reflecting the 60-cent premium in effect in Singapore at the time—but rose considerably for larger time savings such as 15 minutes, since riders may not respond much to savings of only 5-10 minutes.

A.3 Self-reported electric-bus experience

In the baseline, the second and fourth online rounds, and the endline, participants answered two questions about their experience with electric buses. The first asked whether they could "name any public bus service numbers in Singapore that use electric buses." Those who answered affirmatively were prompted to provide a service number. We define a dummy equal to 1 if the participant named an electric bus service.

The second question asked whether they had "ever traveled on an electric bus in Singapore," with a "Don't know" option. Those who answered affirmatively were asked to specify a service number or select "Yes, but don't recall bus service number." We define a dummy equal to 1 if the participant self-reported having traveled on an electric bus.

Table A1 shows that, at baseline, 31% of participants named an electric bus service and 41% self-reported having traveled on one. Over 95% of those who named an electric bus had service stopping at their block, pointing to the key role of firsthand exposure.

A.4 Model estimation and WTP for electric bus rides

From equation 7, the observed utility components are:

$$\begin{aligned} V_{ijt}^{BT,r} &= \beta_{1i}^{r} electricBus_{ijt} + \beta_{3i}^{BT,r} rideTime_{ijt} + \beta_{4i} walkTime_{ijt} + \delta_{j}^{BT,r} \quad \text{if } t \in \mathcal{T}^{BT}, \\ V_{ijt}^{VOT,r} &= \beta_{2i} fare_{ijt} + \beta_{3i}^{VOT,r} rideTime_{ijt} + \delta_{j}^{VOT,r} \quad \text{if } t \in \mathcal{T}^{VOT}. \end{aligned} \tag{A.11}$$

Let $\mathcal{T}_i^{BT,r}$ and $\mathcal{T}_i^{VOT,r}$ denote the sets of bus-type-time and value-of-time tasks completed by participant i in round r. Recall that $\kappa^r = \zeta^{VOT,r}/\zeta^{BT,r}$, and normalize $\zeta^{BT,baseline} = 1$. The probability that participant i chooses alternative j in situation/task t of round r is:

$$P_{ijt}^{r} = \begin{cases} \dfrac{\exp(\zeta^{BT,r} \cdot V_{ijt}^{BT,r})}{\exp(\zeta^{BT,r} \cdot V_{iAt}^{BT,r}) + \exp(\zeta^{BT,r} \cdot V_{iBt}^{BT,r})} & \text{if } t \in \mathcal{T}_i^{BT,r}, \\ \dfrac{\exp(\zeta^{BT,r} \cdot \kappa^r \cdot V_{ijt}^{VOT,r})}{\exp(\zeta^{BT,r} \cdot \kappa^r \cdot V_{iAt}^{VOT,r}) + \exp(\zeta^{BT,r} \cdot \kappa^r \cdot V_{iBt}^{VOT,r})} & \text{if } t \in \mathcal{T}_i^{VOT,r}. \end{cases} \tag{A.12}$$

Let j_{it}^* be the alternative chosen by participant i in situation t. The joint log-likelihood is:

$$LL(\boldsymbol{\theta}) = \sum_{i=1}^{N} \log \left(\int \prod_{r} \left[\prod_{t_1 \in \boldsymbol{\mathcal{T}}_i^{BT,r}} P_{ij_{it_1}^* t_1}^{r}(\boldsymbol{\theta}) \cdot \prod_{t_2 \in \boldsymbol{\mathcal{T}}_i^{VOT,r}} P_{ij_{it_2}^* t_2}^{r}(\boldsymbol{\theta}) \right] f(\boldsymbol{\theta}|\boldsymbol{\Sigma}) d\boldsymbol{\Sigma} \right). \tag{A.13}$$

The integral lacks a closed-form solution and must be approximated by simulation. Given vector $(\boldsymbol{\beta}, \boldsymbol{\Sigma}_{\boldsymbol{\beta}})$, we draw $\boldsymbol{\beta_i}$ using $K = 500$ Modified Latin Hypercube Sampling (MLHS) draws of $\boldsymbol{\nu_i}$. Let $\boldsymbol{\beta_{ik}}$ denote the

k-th draw of participant i's coefficient vector and $\boldsymbol{\theta_{ik}} = (\boldsymbol{\beta_{ik}}, \boldsymbol{\delta}, \boldsymbol{\kappa}, \boldsymbol{\zeta^{BT}})$. The simulated log-likelihood is:

$$LL(\boldsymbol{\theta}) = \sum_{i=1}^{N} \log \left(\frac{1}{K} \sum_{k=1}^{K} \left\{ \prod_{r} \left[\prod_{t_1 \in \boldsymbol{\mathcal{T}}_i^{BT,r}} P^r_{ij^*_{it_1} t_1}(\boldsymbol{\theta_{ik}}) \cdot \prod_{t_2 \in \boldsymbol{\mathcal{T}}_i^{VOT,r}} P^r_{ij^*_{it_2} t_2}(\boldsymbol{\theta_{ik}}) \right] \right\} \right). \tag{A.14}$$

WTP for electric bus rides. For participant i and draw $\boldsymbol{\beta_{ik}}$, the WTP for electric bus rides in round r is:

$$WTP^r_{ik} = -\frac{\beta^r_{1ik}}{\beta_{2ik}}. \tag{A.15}$$

We summarize overall WTP using the median value across participants and draws, with confidence intervals obtained via the Krinsky-Robb method (Krinsky and Robb, 1986).[23] Median WTP is calculated separately by video treatment status and round (at baseline, the median WTP is calculated across all participants). We test the significance of differences across treatment status and rounds following Poe et al. (2005).

Conditional mean WTP for electric bus rides. Given participant i's observed sequence of choices (denoted Y_i), the conditional mean of WTP for electric bus can be calculated based on the simulated draws in equation A.15:

$$\widehat{\overline{WTP^r_i}} = \sum_{k=1}^{K} \omega_k WTP^r_{ik}, \tag{A.16}$$

where $\omega_k = \frac{L(Y_i|\boldsymbol{\theta_{ik}})}{\sum_{k=1}^{K} L(Y_i|\boldsymbol{\theta_{ik}})}$ and $L(Y_i|\boldsymbol{\theta_{ik}})$ is the likelihood contributed by participant i that equals the term inside the curly brackets in equation A.14.

Heterogeneity of WTP for electric bus rides. To explore how the video treatment effect on WTP systematically varies with participants' characteristics, we use the same empirical strategy as section 3.1. We estimate the following regression:

$$\widehat{\overline{WTP^r_i}} = \beta_1 T_i + \beta_2' \boldsymbol{Z_i} + \beta_3' T_i \boldsymbol{Z_i} + \epsilon^r_i. \tag{A.17}$$

The estimation sample includes WTP estimates in the online and endline rounds. The vector Z_i includes baseline WTP along with the same set of covariates as in equation 3. Then, we apply the Sorted Effects method (Chernozhukov et al., 2018) to explore the video treatment effect heterogeneity and compare the covariates difference between the most and least affected participants.

A.5 Robustness of structural model estimates

Table 2 considers an unbalanced panel in which some participants missed choice experiments in specific online rounds and/or at endline, so the observed increase in estimated WTP could reflect compositional changes in the sample. We address this concern using two alternative samples. The first, labeled the balanced panel, retains the 773 participants who completed—besides the baseline when recruited—the endline,

[23] We take 2,000 draws from the estimated distribution of parameter vector $\boldsymbol{\theta}$, compute the median WTP for each draw, and use the 2.5th and 97.5th percentiles to construct a 95% confidence interval. These draws are used for inference and are distinct from the 500 simulation draws used to approximate the integral in equation A.13.

the third online round (bus-type-time tasks), and at least one of the first or fifth online rounds (value-of-time tasks), ensuring that each participant completed both task types in every round. The second, the strongly balanced panel, further restricts to the 581 participants who completed all seven encounters of the education campaign. Columns 3-6 of Table A8 show that these restrictions yield coefficients very similar to those from the unbalanced panel.

Table 2 reveals some differences between online and in-person rounds. To examine whether contextual differences drive the results, we estimate the model using only the baseline and endline choice situations among the 996 participants who completed both encounters. Columns 7-8 of Table A8 indicate that our findings hold under this restriction.

The top panel of Figure A5 plots median WTP estimates for each alternative sample. The time trends closely track those from the unbalanced panel, suggesting that the main findings are robust to sample composition.

We also conduct sensitivity analyses of model specification, reported in Table A9 with corresponding median WTP estimates in the bottom panel of Figure A5. Columns 3-4 restrict the fare coefficient to be non-random, so that all cross-sectional variation in WTP for electric bus rides arises from heterogeneity in preferences for electric buses (see equation 8). The estimated fare coefficient falls by about one-half, inflating WTP for electric buses (red bars). Columns 5-6 impose time invariance on the ride time coefficient, as assumed for walk time, yielding more conservative WTP estimates (purple bars). Columns 7-8 allow walk time coefficients to vary across rounds, as allowed for ride time. The estimated mean and variance of walk time coefficients at baseline grow; nonetheless, WTP for electric buses remains robust (brown bars). Columns 9-10 introduce normally distributed shocks to the alternative-by-task effects for regular buses. There is substantial heterogeneity in intrinsic preferences for regular buses in the value-of-time tasks, but WTP for electric buses remains stable (pink bars). Finally, in the bus-type-time tasks, bus types were randomized, so one-third of situations compared two bus trips using the same technology, differing only in walk and/or ride time—these help identify the marginal rate of substitution between walk time and ride time. To investigate sensitivity, columns 11-12 drop these same-bus-type situations, yielding larger endline WTP estimates (green bars).

A.6 Tracking public-transport ridership

At baseline, 625 of 1,200 participants provided their current farecard numbers. We successfully linked system-wide public-transport ridership records over two years for 588 of them. Five participants provided two cards, yielding 593 farecards in the data.

We extract bus-stop coordinates (in April 2020, 2021, and 2022) from the LTA website and obtain train-station coordinates from Aun (2021). The second stage of the Thomson-East Coast Line opened in August 2021; the train network then remained unchanged until the end of the 2-year ridership sample in March 2022. For the bus segments of a trip, we calculate travel distance and the number of stops en route using bus route maps, also updated at different time points (LTA, 2021, 2022). For train segments, the actual route is unobserved because passengers do not tap out when transferring between lines. We therefore construct shortest paths between observed departure and arrival stations and calculate travel distance and stops en route along these paths (Aun, 2020, 2021).

We drop ∼1% of farecard-by-segment observations in the ridership data due to missing arrival time, missing departure or arrival location, ride duration exceeding two hours, or implied speed exceeding 55 km/h. Compliance with the tap-in/tap-out regime for buses is very high: only 0.5% of segments (all bus segments) are missing tap-out location. This is because commuters are charged by granular distance bands, and failure to tap out results in the maximum fare being charged. This leaves 435,362 segments charged to the 593 farecards (held by 588 participants) across 730 dates.

Following Fesselmeyer et al. (2024), we combine consecutive segments into a single trip if the next segment departs within 15 minutes of the previous segment's arrival. We impose two additional criteria based on the transit agency's fare rules: the maximum duration between the first and last departure within a trip is two hours, and a trip contains at most five segments. We then have a sample of 282,240 trips (Table A12). Trips that include a segment on highly electrified bus service 944 (Figure A7) and on an electric bus (any service; vehicle identified by its license plate) account for 9% and 5% of the data, respectively. These shares rise to 18% and 10% for participants who live right by a stop served by the 944.

We aggregate the data to the participant-week level. An active week for a participant is a calendar week with one or more trips. We exclude three participants with only one active week in the 2-year ridership data and five with no trips prior to their baseline interview. The aggregation produces a balanced panel of 580 participants over 104 weeks (60,320 participant-week observations), of which 33,916 are active weeks (Table A13). Participants used the farecards whose numbers they provided in 58 of the 104 weeks on average. (We miss other public-transport rides they may have paid, for example, with farecards that they lost prior to the baseline interview.)

Ridership versus self-reported travel and electric-bus experience. We use the linked farecard records to assess self-reported public-transport usage (Figure 1). First, comparing self-reported daily trips with trip segments observed from farecards in the week before the baseline (and endline) interviews, we find that participants overstate their trips, with similar bias at baseline and endline (Figure A19). Second, comparing self-reported electric-bus experience with farecard data, participants tend to over-report, especially in the video treatment group (Figure A20). These patterns may reflect recall bias, underscoring the importance of administrative records for examining behavioral changes.

A.7 Robustness of electric-bus ridership estimates

We test the robustness of Figure 7. Some participants have no travel records on their farecards early in the pre-treatment window—e.g., they may have lost their farecard and obtained a new one before the baseline, when they provided the new farecard's number (Appendix A.6). Similarly, some participants have no travel in later weeks of the 2-year ridership data—e.g., due to losing their reported farecard after the baseline. Results are robust to reclassifying zero-travel-record participant-week observations in the balanced panel (Table A13) as missing, thereby restricting the sample to observations with active travel records (Figure A11); to using not-yet-treated rather than never-treated units as the comparison group (Figure A12); and to alternative DiD estimators (Figure A13).

Some treated participants skipped online rounds or missed the endline (Table A2). Based on the encounters each completed, we calculate total minutes of video education received—the "dose"—and implement the continuous DiD estimator of Callaway et al. (2025), which requires auxiliary identification as-

sumptions (omitted for brevity) and collapses observations to two periods: pre-baseline and post-endline. Comparing changes in before-versus-after averages between treated participants at varying doses and the non-video group yields dose-specific DiD estimates of the average treatment effect on the treated. Figure A14 reveals a sensible dose-response pattern: modest exposure did not generate lasting increases in electric-bus use during the post-campaign period, whereas participants exposed to more than five minutes of video exhibited sustained gains. Persistent treatment effects thus required repeated exposure to the educational videos.

Table A1: Balance tests on baseline characteristics, before treatment

Variable at baseline, t_1	Non-video group (1)	Video group (2)	Difference (1)-(2) (3)	p-value (1)=(2) (4)	FDR sharp. q-value (5)
A. Participant characteristics					
Interview duration (minutes)	21.63	22.40	-0.76	0.189	0.898
	(0.42)	(0.40)			
Hour the interview started	15.30	15.40	-0.10	0.448	0.898
	(0.10)	(0.09)			
Participant age (years)	38.85	38.30	0.55	0.416	0.898
	(0.49)	(0.47)			
Participant is female (yes=1)	0.54	0.51	0.03	0.296	0.898
	(0.02)	(0.02)			
Education attainment:					
Below secondary (yes=1)	0.05	0.04	0.01	0.473	0.898
	(0.01)	(0.01)			
Secondary (yes=1)	0.21	0.19	0.01	0.534	0.971
	(0.02)	(0.02)			
Post-secondary and Diploma (yes=1)	0.35	0.41	-0.05*	0.051	0.840
	(0.02)	(0.02)			
Bachelor's and above (yes=1)	0.39	0.36	0.03	0.258	0.898
	(0.02)	(0.02)			
Participant is employed (yes=1)	0.82	0.85	-0.03	0.163	0.898
	(0.02)	(0.01)			
Participant has a driving license (yes=1)	0.54	0.60	-0.05*	0.065	0.840
	(0.02)	(0.02)			
Number of travel days in SG in the preceding week	4.16	4.15	0.00	0.976	1.000
	(0.10)	(0.10)			
Number of trips in a typical day (self-reported)	3.91	4.00	-0.09	0.461	0.898
	(0.09)	(0.09)			
Public-transport share of trips in a typical day (self-reported)	0.63	0.61	0.02	0.433	0.898
	(0.02)	(0.02)			
Car (owned or not) share of trips in a typical day (self-report)	0.25	0.28	-0.02	0.335	0.898
	(0.02)	(0.02)			
B. Household characteristics					
Household size (persons)	3.33	3.40	-0.07	0.404	1.000
	(0.06)	(0.05)			
Married couple (yes=1)	0.72	0.71	0.01	0.646	1.000
	(0.02)	(0.02)			
Has children aged ≤ 5 years (yes=1)	0.28	0.33	-0.05*	0.066	1.000
	(0.03)	(0.03)			
Dwelling type (number of rooms)	3.87	3.86	0.01	0.879	1.000
	(0.04)	(0.04)			
Employs a domestic helper (yes=1)	0.07	0.10	-0.03	0.104	1.000
	(0.01)	(0.01)			
A household member has a respiratory disease (yes=1)	0.06	0.07	-0.01	0.545	1.000
	(0.01)	(0.01)			
Closest stop is served by electric buses (yes=1)	0.51	0.49	0.02	0.564	0.695
	(0.02)	(0.02)			
Number of air-conditioners owned	2.65	2.62	0.04	0.677	1.000
	(0.06)	(0.06)			
Number of PC/tablets owned	2.24	2.25	-0.01	0.881	1.000

Variable at baseline, t_1	Non-video group (1)	Video group (2)	Difference (1)-(2) (3)	p-value (1)=(2) (4)	FDR sharp. q-value (5)
	(0.06)	(0.06)			
Owns car(s) (yes=1)	0.37	0.38	-0.01	0.771	1.000
	(0.02)	(0.02)			
C. Other baseline questions					
Uses a Phone App to check	0.75	0.75	0.00	0.959	1.000
bus arrival time (yes=1)	(0.02)	(0.02)			
Identifies diesel as SG public	0.63	0.66	-0.02	0.432	1.000
buses' main engine type (yes=1)	(0.02)	(0.02)			
Environmental beliefs &	-0.00	-0.03	0.03	0.640	1.000
attitudes (index of 13 statements)	(0.04)	(0.04)			
Electric bus satisfaction rel. to	-0.00	-0.02	0.02	0.678	1.000
diesel (index of 6 co-benefits)	(0.04)	(0.04)			
Able to name an electric	0.32	0.30	0.02	0.389	1.000
public bus service (yes=1)	(0.02)	(0.02)			
Self-reports having traveled	0.41	0.41	0.01	0.825	1.000
in an electric bus (yes=1)	(0.02)	(0.02)			
Joint orthogonality test				0.712	
Number of participants ($N = 1200$)	576	624			

Notes: Columns 1 and 2 report each variable's mean (or proportion if binary) and standard error (in parentheses), by group. Column 3 reports the mean difference between groups, and column 4 reports the p-value from a two-sided t-test. Column 5 reports the FDR-sharpened q-value, which adjusts the p-value within each panel for multiple-hypothesis testing (Anderson, 2008). The bus-arrival-app question was asked only of participants who self-reported using public transport (520 in the non-video group and 487 in the video group). The joint orthogonality test reports the p-value from an F-test of a regression of the video-treatment indicator on all variables (panels A to C). This joint test provides an overall assessment of balance between groups across all reported variables. Significant at *10%, **5%, ***1%.

Table A2: Attrition and completion times are not affected by treatment

	Endline, t_7		Online, t_2 to t_6		
	(1)	(2)	(3)	(4)	
A. Attrition rate					
Video treatment	-0.010	-0.012	-0.003	-0.009	
	(0.022)	(0.022)	(0.029)	(0.028)	
Participant covariates		✓		✓	
Attrition rate of non-video group	0.175	0.175	0.477	0.477	
Number of participants	1200	1200	1200	1200	
B. Completion time (minutes)					
Video treatment	-0.407	-0.363	1.070	1.221	
	(0.443)	(0.439)	(0.958)	(0.966)	
Participant covariates		✓		✓	
Completion time of non-video group	12.440	12.440	16.201	16.201	
Number of participants	996	996	629	629	
	First online t_2	Second online t_3	Third online t_4	Fourth online t_5	Fifth online t_6
	(5)	(6)	(7)	(8)	(9)
C. Attrition rate					
Video treatment	-0.026	-0.020	-0.001	-0.016	0.002
	(0.026)	(0.025)	(0.024)	(0.025)	(0.025)
Participant covariates	✓	✓	✓	✓	✓
Attrition rate of non-video group	0.333	0.276	0.245	0.288	0.281
Number of participants	1200	1200	1200	1200	1200

Notes: This table tests whether the video treatment affected participants' attrition and completion times in the endline and online encounters. In panel A, the dependent variable is an indicator for failing to complete the endline interview (columns 1 and 2) or any of one the five online encounters (columns 3 and 4). In panel B, the dependent variable is completion time (minutes) for the endline interview (996 participants) or total time spent across the five online encounters (for the 629 participants who completed all online encounters); we deduct the mechanical video screening time from the video group's completion time. In panel C, the dependent variable is an indicator for failing to complete an online encounter. Columns 1 and 3 report unconditional differences between the video and non-video groups, while columns 2, 4, and 5-9 control for baseline interview completion time and participant characteristics: indices of environmental attitudes and electric-bus satisfaction, total daily trips, and the shares of public-transit and car trips (all measured at baseline, t_1), as well as age, gender, bachelor's degree, employment status, car ownership, income, the presence of children under six years old, and proximity to electric-bus stops. Heteroskedasticity-robust standard errors are reported in parentheses. Significant at *10%, **5%, and ***1%.

Table A3: Questions on assessing environmental beliefs and attitudes

	% participants (only baseline shown here, $N = 1200$)				
Statements	Strongly Disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly Agree (5)
a. With our current lifestyles, humans are abusing the environment.	0	5	20	59	16
b. Animals and plants have as much right as humans to exist.	1	4	25	49	22
c. Humans are meant to rule over the rest of nature.	7	33	32	20	8
d. The so-called "climate crisis" facing humans has been exaggerated.	10	31	26	27	6
e. Our climate is warming, rainfall is becoming less reliable, and sea levels are rising.	1	3	13	55	28
f. Humans are responsible for global warming and climate change.	0	2	11	55	32
g. I feel anxious about what global warming, climate change, and rising sea levels will do to us.	1	5	29	49	16
h. Policies to protect the environment are very important for Singapore's government to consider.	0	2	15	55	27
i. Actions to reduce our impact on the environment are very important for Singapore's shoppers to consider.	0	2	16	56	26
j. We do not need to change our lifestyles to address climate change because science and technology alone will provide solutions.	16	43	19	14	7
k. We should leave future Singaporeans at least as well off as we are.	2	6	25	50	17
l. I care about air pollution (such as the PSI) and its effect on the respiratory health of my family.	0	2	16	54	27
m. Road vehicles, including public buses, are a major source of air pollutants such as PM2.5.	0	6	22	53	19

Notes: Statements used to measure environmental beliefs and attitudes. The 13 statements were administered in both the baseline and endline interviews, after the choice experiments (Figure 1). The table reports the distribution of baseline responses across five categories: Strongly Disagree, Disagree, Neutral, Agree, and Strongly Agree. Statements (a)-(d) are adapted from Dunlap et al. (2000), statement (e) from Deryugina and Shurchkov (2016), statement (f) from Attari et al. (2010), and statement (g) from Verplanken and Roy (2016); statements (h)-(m) were developed by the authors. In constructing the summary index of environmental beliefs and attitudes (Anderson, 2008), we reverse-code responses to statements (c), (d), and (j) so that higher values consistently indicate more pro-environmental attitudes.

Table A4: Subjects in the video treatment were generally attentive

A. Quiz questions asked in more than one encounter (proportion answering correctly)	Baseline interview, t_1 (1)	Fifth online, t_6 (6)	Endline interview, t_7 (7)	Difference (6)-(1) or (7)-(1)	p-value (6)=(1) or (7)=(1)
1(One diesel bus in SG releases 200 tons CO_2 per year)	0.87 (0.01)		0.94 (0.01)	0.06***	0.000
1(One electric bus in SG releases 100 tons CO_2 per year)	0.90 (0.01)		0.92 (0.01)	0.02	0.220
1(Electric bus releases less CO_2, less fumes, is quieter)		0.98 (0.01)	0.96 (0.01)	-0.02**	0.048
Number of participants	624	442	519		
B. Quiz questions asked in only one encounter (proportion answering correctly)	First online, t_2 (2)	Second online, t_3 (3)	Third online, t_4 (4)	Fourth online, t_5 (5)	
1(Diesel bus releases more CO_2 than electric bus)	0.94				
1(Cars are the transport mode that emits more than buses)		0.81			
1(Diesel bus emits more fumes and PM2.5 than electric bus)			0.95		
1(Electric bus is quieter, neighborhood-friendly than diesel bus)				0.96	
Number of participants	430	466	469	452	

Notes: Quiz questions were:
At t_1 and t_7: Select the CO_2 quantity released by each bus type: Subquestion 1 (subquestion 2): How much CO_2 does one diesel (electric) bus used in Singapore release in one year? Tons of CO_2 released (a global warming gas) $\in$ {100, 200, Don't know}.
At t_2: Which bus type releases more CO_2 that causes climate change such as hotter weather, a rising sea level, and heavy rain? {Diesel bus, Electric bus, Don't know}
At t_3: Which transport mode releases more CO_2 that causes climate change such as hotter weather, a rising sea level, and heavy rain? {Private car w/ just me inside, Public bus w/ many people, Don't know}.
At t_4: Which bus type releases more fumes containing very small particles (PM2.5) that are bad for your health? {Diesel bus, Electric bus, Don't know}.
At t_5: Which bus type is quieter, benefiting people in your neighbourhood? {Diesel bus, Electric bus, Don't know}.
At t_6: Which bus type releases less climate-changing CO_2, releases less harmful fumes, and is quieter for residents and riders? {Diesel bus, Electric bus, Don't know}.

Table A5: Video scripts (videos available via this YouTube link)

Encounter	Video script	
Baseline, t_1	Climate change. It's caused by greenhouse gases like CO_2, which traps heat from the sun, increases temperatures, and leads to all sorts of weather and environmental changes, like rising sea levels. One MAJOR source of CO_2 in Singapore are our buses, most of which run on diesel fuel. Diesel releases CO_2 when burned. Each bus releases 200 tons of CO_2 per year. Now that's a LOT of CO_2. You know what doesn't release a lot of CO_2? Electric buses which run on ELECTRICITY. Each electric bus releases only 100 tons of CO_2 emissions per year, only HALF of a diesel bus. For scale, this here is a fully grown rain tree. HUGE isn't it? If I burned it all, it would release 10 tons of CO_2 into the air. Changing just one diesel bus to an electric one is equivalent to saving 10 of these fully grown trees EVERY YEAR. Wow, that's a LOT of trees.	https://youtu.be/O8TsPen7jgI
First online, t_2	Diesel comes from oil which releases CO_2 when used. CO_2 causes climate change, which is BAD. Climate change leads to hotter weather, a rising sea level and extreme weather patterns like really heavy rains and dry spells. Which is BAD. You know what isn't bad? Electric buses. Remember that replacing just one diesel bus with an electric one stops adding 100 tons of CO_2 to our air EVERY YEAR. That's like saving 10 big trees from burning. Imagine if we replaced all our diesel buses with electric ones, how much CO_2 we'd save in terms of trees. That's a LOT of trees.	https://youtu.be/5-XYq8Z9IMk
Second online, t_3	Cars. Very costly for drivers and for the environment. Most cars use petrol. Petrol comes from oil which releases CO_2. One petrol car releases 10 tons of CO_2 when driven for a year. That's the same amount of CO_2 released if we burned down one big tree. If instead of taking the car I ride the bus, I will save 10 tons of CO_2 in a year. If 10 drivers switch to riding the bus, this stops adding 100 tons of CO_2 to our air. Want more? If the bus is electric instead of diesel, that saves another 100 tons of CO_2 per year. Less petrol cars, less diesel buses, and more electric buses, are choices that reduce CO_2 and protect our climate.	https://youtu.be/BijsVyF3cls
Third online, t_4	Electric buses release only HALF the CO_2 compared with diesel buses. This protects our climate, our rainfall, and our sea level. Which is GOOD. You know what else is GOOD? Electric buses have NO tailpipe and NO fumes. In contrast, diesel buses have tailpipes and their fumes contain lots of tiny particles, like PM2.5, that enter your lungs and make your health not so good. Get that stinky diesel bus out of my face! Because electric buses have no fumes, the air at the bus stop and in our neighborhood is cleaner and healthier. No more having to hold your breath as those diesel buses leave the bus stop!	https://youtu.be/4txILxxSeEM
Fourth online, t_5	[Noise of regular bus drowns out audio to make salient how noisy diesel buses are, subtitles keep message clear.] Electric buses release only HALF the CO_2 compared with diesel buses. This protects our climate, our rainfall, and our sea level. Because electric buses have NO fumes that enter your lungs, air in our neighborhood is cleaner and healthier. Oh my god this is so annoying, I can't hear anything. [Snap transition into inside an electric bus; no audio recorded here, only ambient sound of electric bus traveling.] Ahh much better. You know what else is GOOD? Electric buses are quieter as they go around the neighborhood. Rides are more relaxing without that loud engine sound in your ears, isn't it? It is easier to listen to music or talk to your friends when in the bus or outside as it passes by. They're so quiet they might just leave before you even realized they were here.	https://youtu.be/NHLyGWkwCvs
Fifth online, t_6	Now some of you might be thinking, "Aren't electric buses expensive?" Well, yes and no. It's true, electric buses cost more than diesel buses when you buy them. However, many agencies have found that electric buses are cheaper to maintain over time. They break down less, and electricity is cheaper than diesel. So why are electric buses GOOD? They release less CO_2, which protects our climate. They have no fumes, so air in our neighborhood is cleaner and healthier. They are quieter, which is also better for everyone. Yeah, add these benefits to less breakdowns and cheaper electricity, and I think we have a clear winner on which bus is better.	https://youtu.be/ikHM1rio7GY
Endline, t_7	Protecting our climate is in our hands, as is preserving our rainfall and our sea level! One great way to do this is to use cleaner buses. Each year, one electric bus releases 100 tons of CO_2 compared with 200 tons of CO_2 for a diesel bus. Electric buses release only HALF the CO_2 compared with diesel buses. Electric buses protect our climate. [Appears one by one on the screen: Less CO_2 → Protect climate. Less fumes → Protect our lungs. Less noise → Protect our mental health. Cheaper to run → Protect public funds On-screen list of co-benefits.] Electric buses have NO tailpipe and NO fumes. Less PM2.5 in our neighborhood protects our lungs. Electric buses are quieter. Less noise in our neighborhood protects our mental health. Electric buses are more expensive to buy but they break down less and are cheaper to run. Over time, they are a GOOD investment. Singapore has 4000 buses, means we can save the equivalent CO_2 that is stored in 40,000 trees, EVERY YEAR, which is a lot of trees.	https://youtu.be/gb9N9MmCLRo

Table A6: Average treatment effects on electric-bus satisfaction (balanced sample)

Dependent variable:	Electric-bus satisfaction versus diesel buses						
	Less CO_2 emissions	Less climate change	Less fumes	Quieter travel	More reliable service	Better for the environment	Satisfaction summary index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Electric-bus satisfaction relative to diesel bus (5-point scale, Strongly (Dis)Agree = (-2) 2, randomized order)							
Video treatment	0.23***	0.25***	0.19***	0.23***	0.22***	0.22***	0.21***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)
Mean at baseline, t_1	1.02	0.98	1.14	1.05	0.38	1.06	0.05
Std. dev. at baseline	1.25	1.27	1.29	1.25	1.15	1.27	0.94
B. Agree/Strongly Agree that electric bus outperforms diesel bus (yes = 1, randomized order)							
Video treatment	0.07***	0.07***	0.05***	0.09***	0.09***	0.06***	
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	
Mean at baseline, t_1	0.70	0.70	0.76	0.71	0.37	0.72	
Std. dev. at baseline	0.46	0.46	0.43	0.45	0.48	0.45	
Number of participants	716	716	716	716	716	716	716
Number of observations	2146	2146	2146	2146	2146	2146	2146

Notes: OLS estimates of equation 1 in a balanced sample of 716 participants who completed all encounters in which electric-bus satisfaction was elicited (Figure 1). Other notes in the caption of Table 1 apply here. Significant at *10%, **5%, and ***1%.

Table A7: Combinatorial tests for differences in WTP across rounds and in non-video vs. video treatment

H_0 comparison	p-value	BH adj. p-value
Video treatment: online < baseline	0.000	0.000
Non-video: online < baseline	0.002	0.004
Video treatment: endline < baseline	0.000	0.000
Non-video: endline < baseline	0.012	0.024
Video treatment: endline < online	0.764	0.764
Non-video: endline < online	0.655	0.749
Video treatment < Non-video, online	0.022	0.035
Video treatment < Non-video, endline	0.078	0.104

Notes: This table reports combinatorial test results (Poe et al., 2005); the sample is that of Table 2. We show the p-value for the null hypothesis in the H_0 comparison column, both without and with a Benjamini-Hochberg adjustment for multiple hypotheses within each panel. Video treatment refers to participants assigned to the video group; non-video refers to participants who never watched the educational videos.

Table A8: Robustness of structural model estimates to different samples

	Unbalanced panel		Balanced panel		Strongly balanced		Balanced, base & end	
	Estimate (1)	S.E. (2)	Estimate (3)	S.E. (4)	Estimate (5)	S.E. (6)	Estimate (7)	S.E. (8)
Mean effects (β)								
Electric bus, baseline ($\beta_{10}^{baseline}$)	0.585***	(0.084)	0.620***	(0.108)	0.574***	(0.117)	0.588***	(0.097)
Electric bus, online (β_{10}^{online})	0.977***	(0.125)	1.063***	(0.148)	1.042***	(0.155)		
Electric bus, endline ($\beta_{10}^{endline}$)	0.983***	(0.143)	1.024***	(0.164)	1.010***	(0.181)	0.966***	(0.151)
Electric bus, online × Video T (β_{11}^{online})	0.356***	(0.135)	0.337**	(0.154)	0.464***	(0.168)		
Electric bus, endline × Video T (β_{11}^{endl})	0.292*	(0.155)	0.315*	(0.175)	0.360*	(0.204)	0.316**	(0.152)
Bus fare (β_{20})	-0.032***	(0.004)	-0.034***	(0.006)	-0.033***	(0.005)	-0.032***	(0.005)
Ride time, baseline ($\beta_{30}^{baseline}$)	-0.236***	(0.040)	-0.250***	(0.038)	-0.265***	(0.043)	-0.227***	(0.040)
Ride time, online (β_{30}^{online})	-0.190***	(0.031)	-0.210***	(0.032)	-0.201***	(0.033)		
Ride time, endline ($\beta_{30}^{endline}$)	-0.201***	(0.052)	-0.219***	(0.037)	-0.215***	(0.038)	-0.195***	(0.033)
Walk time (β_{40})	-0.499***	(0.059)	-0.496***	(0.066)	-0.494***	(0.070)	-0.595***	(0.089)
Standard deviation and correlation (Σ_β)								
Std.dev. electric bus, baseline	0.789***	(0.234)	0.829***	(0.295)	0.558	(0.438)	0.810***	(0.300)
Std.dev. electric bus, online	0.481**	(0.205)	0.581***	(0.177)	0.411*	(0.225)		
Std.dev. electric bus, endline	1.008***	(0.176)	0.982***	(0.200)	0.964***	(0.231)	0.998***	(0.170)
Std.dev. bus fare	0.027***	(0.004)	0.026***	(0.005)	0.024***	(0.004)	0.036***	(0.005)
Std.dev. ride time, baseline	0.201***	(0.029)	0.194***	(0.030)	0.219***	(0.033)	0.225***	(0.037)
Std.dev. ride time, online	0.083***	(0.029)	0.084***	(0.019)	0.061***	(0.015)		
Std.dev. ride time, endline	0.170**	(0.069)	0.147***	(0.031)	0.130***	(0.027)	0.180***	(0.031)
Std.dev. walk time	0.513***	(0.069)	0.411***	(0.063)	0.384***	(0.063)	0.771***	(0.124)
Corr., walk time & ride time, basel	0.213*	(0.110)	0.247***	(0.066)	0.180**	(0.076)	0.168***	(0.051)
Corr., walk time & ride time, online	0.417***	(0.143)	0.481***	(0.112)	0.489***	(0.172)		
Corr., walk time & ride time, endline	0.215**	(0.087)	0.285***	(0.071)	0.245***	(0.091)	0.180***	(0.064)
Alternative-by-task effects (δ)								
$\delta_A^{BT,baseline}$ (left bias)	-0.113*	(0.059)	-0.124*	(0.074)	-0.159*	(0.084)	-0.106	(0.066)
$\delta_A^{BT,online}$ (left bias)	0.055	(0.047)	0.054	(0.053)	0.106*	(0.058)		
$\delta_A^{BT,endline}$ (left bias)	0.055	(0.052)	0.037	(0.060)	0.061	(0.071)	0.057	(0.050)
$\delta_A^{VOT,baseline}$ (pref. regular bus)	0.490***	(0.080)	0.463***	(0.103)	0.568***	(0.122)	0.465***	(0.087)
$\delta_A^{VOT,online}$ (pref. regular bus)	0.533***	(0.084)	0.568***	(0.093)	0.483***	(0.090)		
$\delta_A^{VOT,endline}$ (pref. regular bus)	0.280***	(0.082)	0.315***	(0.096)	0.244**	(0.108)	0.352***	(0.089)
Scale factors (κ, ζ^{BT})								
$\kappa^{baseline} = \zeta^{VOT,basel}/\zeta^{BT,basel}$	2.202***	(0.285)	1.901**	(0.316)	1.982**	(0.366)	2.764***	(0.437)
$\kappa^{online} = \zeta^{VOT,online}/\zeta^{BT,online}$	0.923	(0.120)	0.880	(0.112)	0.872	(0.122)		
$\kappa^{endline} = \zeta^{VOT,endl}/\zeta^{BT,endl}$	1.118	(0.173)	1.063	(0.172)	1.080	(0.201)	0.968	(0.169)
$\zeta^{BT,online}$	1.892***	(0.229)	1.885***	(0.246)	2.098***	(0.321)		
$\zeta^{BT,endline}$	1.705**	(0.214)	1.675**	(0.240)	1.585*	(0.253)	2.015**	(0.308)
Number of participants	1200		773		581		996	
Number of observations	13,930		10,570		8134		7968	
Number of estimated parameters	30		30		30		21	
Log-likelihood	-7044.6		-5225.5		-3972.7		-4176.4	
Adjusted ρ^2	0.267		0.283		0.290		0.240	
AIC	14,149.3		10,511.0		8005.4		8394.8	

Notes: Random-coefficients model estimates of equation 5 using different samples. Columns 1-2 reproduce columns 3-4 of Table 2 based on all choice situations presented to the 1200 recruited participants. Columns 3-4 restrict the sample to 773 participants who completed—besides the baseline upon recruitment—the endline, the third online round (bus-type-time tasks), and at least one of the first or fifth online rounds (value-of-time tasks). Columns 5-6 further restrict the sample to the 581 participants who completed all seven encounters (thus $581 \times (4+2+2+2+4)$ choice situations at baseline; first, third, and fifth online; and endline). Columns 7-8 use only the baseline and endline choice situations among the 996 participants who completed both encounters. Other notes follow Table 2. Significant at *10%, **5%, and ***1%.

Table A9: Robustness of structural model estimates to different specifications

	Main specification (random coeff.)		Non-random fare coefficient		Ride time coefficient is time invariant		Walk time coefficient varies by round		Alternative effects for regular bus are random		Drop BT choice situations with same bus type	
	Estimate (1)	S.E. (2)	Estimate (3)	S.E. (4)	Estimate (5)	S.E. (6)	Estimate (7)	S.E. (8)	Estimate (9)	S.E. (10)	Estimate (11)	S.E. (12)
Mean effects (β)												
Electric bus, baseline ($\beta_{10}^{baseline}$)	0.585***	(0.084)	0.503***	(0.073)	0.590***	(0.086)	0.644***	(0.097)	0.595***	(0.085)	0.611***	(0.094)
Electric bus, online (β_{10}^{online})	0.977***	(0.125)	0.962***	(0.115)	1.128***	(0.138)	0.846***	(0.143)	1.128***	(0.137)	0.700***	(0.125)
Electric bus, endline ($\beta_{10}^{endline}$)	0.983***	(0.143)	0.837***	(0.115)	1.034***	(0.146)	0.919***	(0.180)	1.015***	(0.144)	1.120***	(0.220)
Electric bus, online × Video T (β_{11}^{online})	0.356***	(0.135)	0.298**	(0.131)	0.374**	(0.153)	0.263**	(0.120)	0.370**	(0.148)	0.255**	(0.102)
Electric bus, endl × Video T ($\beta_{11}^{endline}$)	0.292*	(0.155)	0.289**	(0.134)	0.350**	(0.164)	0.361**	(0.150)	0.338**	(0.162)	0.309*	(0.178)
Fare (β_{20})	-0.032***	(0.004)	-0.017***	(0.001)	-0.041***	(0.005)	-0.032***	(0.005)	-0.040***	(0.005)	-0.026***	(0.005)
Ride time, baseline ($\beta_{30}^{baseline}$)	-0.236***	(0.040)	-0.192***	(0.030)			-0.267***	(0.045)	-0.243***	(0.027)	-0.214***	(0.049)
Ride time, online (β_{30}^{online})	-0.190***	(0.031)	-0.159***	(0.023)			-0.176***	(0.032)	-0.221***	(0.023)	-0.141***	(0.029)
Ride time, endline ($\beta_{30}^{endline}$)	-0.201***	(0.052)	-0.169***	(0.029)			-0.194***	(0.039)	-0.213***	(0.028)	-0.171***	(0.042)
Ride time (β_{30})					-0.225***	(0.025)						
Walk time (β_{40})	-0.499***	(0.059)	-0.347***	(0.039)	-0.519***	(0.056)			-0.514***	(0.057)	-0.924***	(0.269)
Walk time, baseline ($\beta_{40}^{baseline}$)							-2.544**	(1.022)				
Walk time, online (β_{40}^{online})							-0.524***	(0.136)				
Walk time, endline ($\beta_{40}^{endline}$)							-0.641***	(0.189)				
Standard deviation and correlation (Σ_β)												
Std.dev. electric bus, baseline	0.789***	(0.234)	0.665***	(0.226)	0.919***	(0.226)	0.871***	(0.262)	0.763***	(0.255)	0.727***	(0.271)
Std.dev. electric bus, online	0.481**	(0.205)	0.593***	(0.148)	0.662***	(0.169)	0.530***	(0.146)	0.592***	(0.170)	0.479***	(0.117)
Std.dev. electric bus, endline	1.008***	(0.176)	0.849***	(0.150)	1.086***	(0.169)	0.870***	(0.189)	1.113***	(0.174)	0.902***	(0.249)
Std.dev. fare	0.027***	(0.004)			0.036***	(0.005)	0.027***	(0.004)	0.035***	(0.005)	0.022***	(0.004)
Std.dev. ride time, baseline	0.201***	(0.029)	0.214***	(0.028)			0.259***	(0.043)	0.123***	(0.034)	0.231***	(0.048)
Std.dev. ride time, online	0.083***	(0.029)	0.112***	(0.016)			0.059***	(0.015)	0.037**	(0.015)	0.038***	(0.014)
Std.dev. ride time, endline	0.170**	(0.069)	0.164***	(0.027)			0.140***	(0.034)	0.137***	(0.035)	0.149***	(0.034)
Std.dev. ride time					0.100***	(0.017)						
Std.dev. walk time	0.513***	(0.069)	0.219***	(0.040)	0.495***	(0.061)			0.473***	(0.061)	2.247***	(0.755)
Std.dev. walk time, baseline							13.864**	(6.551)				
Std.dev. walk time, online							0.699***	(0.198)				
Std.dev. walk time, endline							0.906***	(0.298)				
Corr., walk time & ride time, baseline	0.213*	(0.110)	0.459***	(0.053)			0.047	(0.030)	0.277***	(0.106)	0.062	(0.069)

	Main specification (random coeff.)		Non-random fare coefficient		Ride time coefficient is time invariant		Walk time coefficient varies by round		Alternative effects for regular bus are random		Drop BT choice situations with same bus type	
	Estimate (1)	S.E. (2)	Estimate (3)	S.E. (4)	Estimate (5)	S.E. (6)	Estimate (7)	S.E. (8)	Estimate (9)	S.E. (10)	Estimate (11)	S.E. (12)
Corr., walk time & ride time, online	0.417***	(0.143)	0.724***	(0.062)			0.285**	(0.128)	0.839***	(0.305)	0.248	(0.268)
Corr., walk time & ride time, endline	0.215**	(0.087)	0.530***	(0.057)			0.130**	(0.065)	0.217***	(0.073)	0.077	(0.088)
Corr., walk time & ride time					0.458***	(0.100)						
Alternative-by-task effects (δ)												
$\delta_A^{BT,baseline}$ (left bias)	-0.113*	(0.059)	-0.095*	(0.053)	-0.111*	(0.059)	-0.109	(0.067)	-0.118**	(0.059)	-0.095	(0.076)
$\delta_A^{BT,online}$ (left bias)	0.055	(0.047)	0.071	(0.044)	0.068	(0.052)	0.040	(0.040)	0.061	(0.051)	-0.014	(0.044)
$\delta_A^{BT,endline}$ (left bias)	0.055	(0.052)	0.071	(0.047)	0.029	(0.054)	0.029	(0.049)	0.047	(0.054)	0.023	(0.082)
$\delta_A^{VOT,baseline}$ (pref. regular bus)	0.490***	(0.080)	0.451***	(0.064)	0.380***	(0.095)	0.624***	(0.099)	0.637***	(0.155)	0.452***	(0.091)
$\delta_A^{VOT,online}$ (pref. regular bus)	0.533***	(0.084)	0.543***	(0.069)	0.638***	(0.086)	0.426***	(0.091)	0.592***	(0.099)	0.340***	(0.075)
$\delta_A^{VOT,endline}$ (pref. regular bus)	0.280***	(0.082)	0.360***	(0.064)	0.404***	(0.095)	0.267***	(0.102)	0.245*	(0.127)	0.281***	(0.088)
Std.dev. $\delta_A^{VOT,baseline}$									2.436***	(0.403)		
Std.dev. $\delta_A^{VOT,online}$									0.733***	(0.142)		
Std.dev. $\delta_A^{VOT,endline}$									1.592***	(0.272)		
Scale factors (κ, ζ^{BT})												
$\kappa^{baseline}$	2.202***	(0.285)	2.974***	(0.337)	0.788	(0.110)	2.146***	(0.321)	1.404	(0.223)	2.530***	(0.429)
κ^{online}	0.923	(0.120)	1.311	(0.158)	0.686***	(0.087)	0.751**	(0.093)	0.861	(0.102)	0.696*	(0.146)
$\kappa^{endline}$	1.118	(0.173)	1.698**	(0.227)	0.593***	(0.084)	1.010	(0.167)	0.863	(0.142)	1.887**	(0.366)
$\zeta^{BT,online}$	1.892***	(0.229)	1.793***	(0.179)	1.754***	(0.198)	2.559***	(0.432)	1.697***	(0.187)	3.513**	(0.867)
$\zeta^{BT,endline}$	1.705**	(0.214)	1.593***	(0.165)	1.564***	(0.180)	2.006**	(0.383)	1.719***	(0.209)	1.306	(0.279)
Number of participants	1200		1200		1200		1200		1200		1171	
Number of observations	13,930		13,930		13,930		13,930		13,930		11,453	
Number of estimated parameters	30		29		26		34		33		30	
Log-likelihood	-7044.6		-7156.2		-7188.5		-7005.7		-6952.4		-5905.4	
Adjusted ρ^2	0.267		0.256		0.253		0.271		0.277		0.252	
AIC	14149.3		14370.5		14428.9		14079.4		13970.8		11870.7	

Notes: Random-coefficients model estimates of equation 5 using different specifications. Columns 1-2 reproduce Table 2, columns 3-4. Columns 3-4 assume a non-random coefficient on the fare. Columns 5-6 assume time-invariant preferences for ride time (like we assume for walk time). Columns 7-8 allow preferences for walk time to vary across rounds (like we assume for ride time). Columns 9-10 allow the alternative-by-task effect of regular buses in the value-of-time task to be random and normally distributed (as we allow for the effect of electric buses in the bus-type-time task). Columns 11-12 drops from the estimation sample bus-type-time choice situations in which the same bus type is compared (diesel vs. diesel or electric vs. electric). Other notes follow Table 2. Significant at *10%, **5%, and ***1%.

Table A10: Balance tests on baseline characteristics, before treatment: 588 participants who provided farecard numbers

Variable at baseline, t_1	Non-video group (1)	Video group (2)	Difference (1)-(2) (3)	p-value (1)=(2) (4)	FDR sharp. q-value (5)
A. Participant characteristics					
Interview duration (minutes)	21.66	22.43	-0.77	0.337	1.000
	(0.59)	(0.54)			
Hour the interview started	15.34	15.45	-0.10	0.596	1.000
	(0.14)	(0.14)			
Participant age (years)	40.88	41.09	-0.21	0.843	1.000
	(0.75)	(0.73)			
Participant is female (yes=1)	0.62	0.59	0.03	0.523	1.000
	(0.03)	(0.03)			
Education attainment:					
Below secondary (yes=1)	0.07	0.06	0.01	0.651	1.000
	(0.01)	(0.01)			
Secondary (yes=1)	0.23	0.27	-0.04	0.216	1.000
	(0.02)	(0.03)			
Post-secondary and Diploma (yes=1)	0.41	0.41	-0.01	0.891	1.000
	(0.03)	(0.03)			
Bachelor's and above (yes=1)	0.30	0.26	0.04	0.274	1.000
	(0.03)	(0.03)			
Participant is employed (yes=1)	0.74	0.80	-0.06*	0.076	1.000
	(0.03)	(0.02)			
Participant has a driving license (yes=1)	0.43	0.45	-0.02	0.576	1.000
	(0.03)	(0.03)			
Number of travel days in SG in the preceding week	4.24	4.34	-0.10	0.604	1.000
	(0.14)	(0.13)			
Number of trips in a typical day (self-reported)	4.14	4.40	-0.26	0.173	1.000
	(0.14)	(0.14)			
Public transport share of trips in a typical day (self-reported)	0.77	0.79	-0.02	0.529	1.000
	(0.02)	(0.02)			
Car (owned or not) share of trips in a typical day (self-report)	0.14	0.13	0.01	0.727	1.000
	(0.02)	(0.02)			
B. Household characteristics					
Household size (persons)	3.41	3.41	-0.00	0.985	1.000
	(0.08)	(0.08)			
Married couple (yes=1)	0.69	0.66	0.03	0.466	1.000
	(0.03)	(0.03)			
Has children aged ≤ 5 years (yes=1)	0.23	0.28	-0.05	0.131	1.000
	(0.02)	(0.03)			
Dwelling type (number of rooms)	3.72	3.63	0.08	0.338	1.000
	(0.06)	(0.06)			
Employs a domestic helper (yes=1)	0.06	0.07	-0.01	0.710	1.000
	(0.01)	(0.02)			
A household member has a respiratory disease (yes=1)	0.07	0.08	-0.01	0.715	1.000
	(0.01)	(0.02)			
Closest stop is served by electric buses (yes=1)	0.46	0.47	-0.01	0.750	1.000
	(0.03)	(0.03)			
Number of air-conditioners	2.37	2.29	0.08	0.506	1.000

Variable at baseline, t_1	Non-video group (1)	Video group (2)	Difference (1)-(2) (3)	p-value (1)=(2) (4)	FDR sharp. q-value (5)
owned	(0.09)	(0.09)			
Number of PC/tablets owned	2.14	2.03	0.11	0.333	1.000
	(0.08)	(0.08)			
Owns car(s) (yes=1)	0.29	0.23	0.06*	0.093	1.000
	(0.03)	(0.02)			
C. Other baseline questions					
Uses a Phone App to check bus arrival time (yes=1)	0.73	0.72	0.01	0.846	1.000
	(0.03)	(0.03)			
Identifies diesel as SG public buses' main engine type (yes=1)	0.61	0.64	-0.03	0.420	1.000
	(0.03)	(0.03)			
Environmental beliefs & attitudes (index of 13 statements)	-0.08	-0.10	0.03	0.734	1.000
	(0.05)	(0.05)			
Electric bus satisfaction rel. to diesel (index over 6 attributes)	-0.04	-0.04	-0.00	0.955	1.000
	(0.06)	(0.06)			
Able to name an electric public bus service (yes=1)	0.35	0.30	0.05	0.230	1.000
	(0.03)	(0.03)			
Self-reports having traveled in an electric bus (yes=1)	0.46	0.42	0.04	0.351	1.000
	(0.03)	(0.03)			
Joint Orthogonality Test				0.819	
Number of Participants ($N = 588$)	296	292			

Notes: Columns 1 and 2 report each variable's mean (proportion if binary) and standard error (in parentheses), by group. Column 3 reports the mean difference across the two groups and column 4 reports the p-value of a two-sided t-test. Column 5 reports the FDR sharpened q-value that adjusts the p-value within each panel for multiple hypotheses testing (Anderson, 2008). The joint orthogonality test refers to the p-value of an F-test of a regression of the video treatment dummy on all variables (panels A to C). This joint test of equality provides an overall evaluation of the balance between the two groups capturing all variables. Significant at *10%, **5%, and ***1%.

Table A11: Baseline charact.: Participants without and with farecards

	Has a farecard?		Difference	p-value	FDR sharp.
Variable at baseline, t_1	No (1)	Yes (2)	(1)-(2) (3)	(1)=(2) (4)	q-value (5)
A. Participant characteristics					
Video group (yes=1)	0.54	0.50	0.05	0.112	0.045
	(0.02)	(0.02)			
Interview duration (minutes)	22.02	22.04	-0.03	0.965	0.149
	(0.42)	(0.40)			
Hour the interview started	15.31	15.39	-0.09	0.531	0.129
	(0.10)	(0.10)			
Participant age (years)	36.24	40.98	-4.74***	0.000	0.001
	(0.42)	(0.52)			
Participant is female (yes=1)	0.44	0.61	-0.16***	0.000	0.001
	(0.02)	(0.02)			
Education attainment:					
Below secondary (yes=1)	0.03	0.07	-0.04***	0.001	0.001
	(0.01)	(0.01)			
Secondary (yes=1)	0.16	0.25	-0.09***	0.000	0.001
	(0.01)	(0.02)			
Post-secondary and Diploma (yes=1)	0.35	0.41	-0.06**	0.042	0.020
	(0.02)	(0.02)			
Bachelor's and above (yes=1)	0.47	0.28	0.19***	0.000	0.001
	(0.02)	(0.02)			
Participant is employed (yes=1)	0.89	0.77	0.12***	0.000	0.001
	(0.01)	(0.02)			
Participant has a driving license (yes=1)	0.70	0.44	0.26***	0.000	0.001
	(0.02)	(0.02)			
Number of travel days in SG in the preceding week	4.02	4.29	-0.27*	0.054	0.023
	(0.10)	(0.10)			
Number of trips in a typical day (self-reported)	3.66	4.27	-0.61***	0.000	0.001
	(0.08)	(0.10)			
Public-transport share of trips in a typical day (self-reported)	0.46	0.78	-0.32***	0.000	0.001
	(0.02)	(0.02)			
Car (owned or not) share of trips in a typical day (self-report)	0.39	0.14	0.25***	0.000	0.001
	(0.02)	(0.01)			
B. Household characteristics					
Household size (persons)	3.32	3.41	-0.09	0.257	0.055
	(0.05)	(0.06)			
Married couple (yes=1)	0.75	0.68	0.07***	0.005	0.005
	(0.02)	(0.02)			
Has children aged ≤ 5 years (yes=1)	0.35	0.26	0.09***	0.000	0.001
	(0.02)	(0.02)			
Dwelling type (number of rooms)	4.04	3.68	0.37***	0.000	0.001
	(0.04)	(0.04)			
Employs a domestic helper (yes=1)	0.10	0.07	0.04**	0.024	0.013
	(0.01)	(0.01)			
A household member has a respiratory disease (yes=1)	0.05	0.07	-0.02	0.168	0.039
	(0.01)	(0.01)			
Closest stop is served by electric buses (yes=1)	0.53	0.47	0.07**	0.021	0.013
	(0.02)	(0.02)			

Variable at baseline, t_1	Has a farecard? No (1)	Yes (2)	Difference (1)-(2) (3)	p-value (1)=(2) (4)	FDR sharp. q-value (5)
Number of air-conditioners owned	2.93	2.33	0.60***	0.000	0.001
	(0.06)	(0.06)			
Number of PC/tablets owned	2.40	2.09	0.32***	0.000	0.001
	(0.06)	(0.06)			
Owns car(s) (yes=1)	0.49	0.26	0.22***	0.000	0.001
	(0.02)	(0.02)			
C. Other baseline questions					
Uses a Phone App to check bus arrival time (yes=1)	0.79	0.72	0.06**	0.024	0.070
	(0.02)	(0.02)			
Identifies diesel as SG public buses' main engine type (yes=1)	0.67	0.62	0.04	0.139	0.104
	(0.02)	(0.02)			
Environmental beliefs & attitudes (index of 13 statements)	0.06	-0.09	0.15**	0.011	0.070
	(0.04)	(0.04)			
Electric-bus satisfaction rel. to diesel (index of 6 co-benefits)	0.01	-0.04	0.05	0.344	0.201
	(0.04)	(0.04)			
Able to name an electric public bus service (yes=1)	0.29	0.33	-0.04	0.127	0.104
	(0.02)	(0.02)			
Self-reports having traveled in an electric bus (yes=1)	0.38	0.44	-0.06**	0.047	0.079
	(0.02)	(0.02)			
Number of participants ($N = 1200$)	612	588			

Notes: Columns 1 and 2 report each variable's mean (or proportion if binary) and standard error (in parentheses), separately for participants without and with farecards. Column 3 reports the mean difference between groups, and column 4 reports the p-value from a two-sided t-test. Column 5 reports the FDR sharpened q-value, which adjusts the p-value within each panel for multiple-hypothesis testing (Anderson, 2008). The bus-arrival-app question was asked only of participants who self-reported using public transport (382 participants without farecards, 425 with). Significant at *10%, **5%, and ***1%.

Table A12: Descriptive statistics for the trip-level farecard data

Variable	Obs.	Mean	S.Dev.	Min.	Max.
All trips					
Number of segments in trip	282,240	1.54	0.70	1.00	6.00
Trip has a single segment (yes=1)	282,240	0.56	0.50	0.00	1.00
Trip has bus segment(s) only (yes=1)	282,240	0.59	0.49	0.00	1.00
Trip has train segment(s) only (yes=1)	282,240	0.13	0.33	0.00	1.00
Trip combines bus and train segments (yes=1)	282,240	0.28	0.45	0.00	1.00
Trip duration w/ transfer (minutes)	282,240	25.83	19.88	0.47	204.60
In-vehicle ride time (minutes)	282,240	23.36	17.68	0.47	182.92
Distance traveled (km)	282,240	8.20	7.31	0.20	78.47
Number of stops en route	282,240	10.72	8.29	1.00	122.00
Workday (yes=1)	282,240	0.75	0.43	0.00	1.00
Trip starts during peak hour (yes=1)	282,240	0.35	0.48	0.00	1.00
COVID-19 pandemic (yes=1)	282,240	0.08	0.27	0.00	1.00
Includes a segment on bus service 944 (yes=1)	282,240	0.09	0.28	0.00	1.00
Includes a segment on an electric bus (yes=1)	282,240	0.05	0.21	0.00	1.00
Only trips made by participants whose immediate bus stop is served by bus 944					
Includes a segment on bus service 944 (yes=1)	132,607	0.18	0.38	0.00	1.00
Includes a segment on an electric bus (yes=1)	132,607	0.10	0.30	0.00	1.00

Notes: Ridership data spanning April 1, 2020 to March 31, 2022, at the farecard-by-trip level, by 588 participants who provided farecard numbers. Any public-transport rides that these participants may have paid with farecards retired prior to—or acquired after—the baseline interview, or paid with bank cards, are not captured. Workdays are non-holiday weekdays (Monday to Friday). Peak hours are trips starting between 7:00 and 9:59 and between 17:00 and 19:59 on workdays. Source: Land Transport Authority.

Table A13: Descriptive statistics for the balanced participant-week level ridership sample

Variable	Obs.	Mean	S.Dev.	Min.	Max.
Participants					
Participant's number of active weeks in 2-year data	580	58.48	30.17	2.00	104.00
Participant is in video treatment group (yes=1)	580	0.50	0.50	0.00	1.00
Trip characteristics, across all weeks					
Participant-week is active (yes=1)	60,320	0.56	0.50	0.00	1.00
Number of (public-transport) trips	60,320	4.67	6.22	0.00	48.00
Trip characteristics, active weeks					
Number of (public-transport) trips	33,916	8.31	6.20	1.00	48.00
Number of bus-only trips	33,916	4.91	4.88	0.00	44.00
Number of train-only trips	33,916	1.07	1.99	0.00	23.00
Number of trips combining bus and train	33,916	2.34	3.01	0.00	20.00
In-vehicle ride time (minutes)	33,916	194.27	176.71	0.95	1474.40
Distance traveled (km)	33,916	68.21	66.76	0.30	546.82
Share of trips that include bus service 944	33,916	0.09	0.21	0.00	1.00
Share of trips that include electric bus	33,916	0.05	0.14	0.00	1.00
Participant-week includes bus service 944 (yes=1)	33,916	0.23	0.42	0.00	1.00
Participant-week includes electric buses (yes=1)	33,916	0.17	0.38	0.00	1.00
Active weeks for participants whose immediate bus stop is served by bus 944					
Share of trips that include bus service 944	15,446	0.19	0.27	0.00	1.00
Share of trips that include electric bus	15,446	0.10	0.19	0.00	1.00
Participant-week includes bus service 944 (yes=1)	15,446	0.50	0.50	0.00	1.00
Participant-week includes electric buses (yes=1)	15,446	0.35	0.48	0.00	1.00

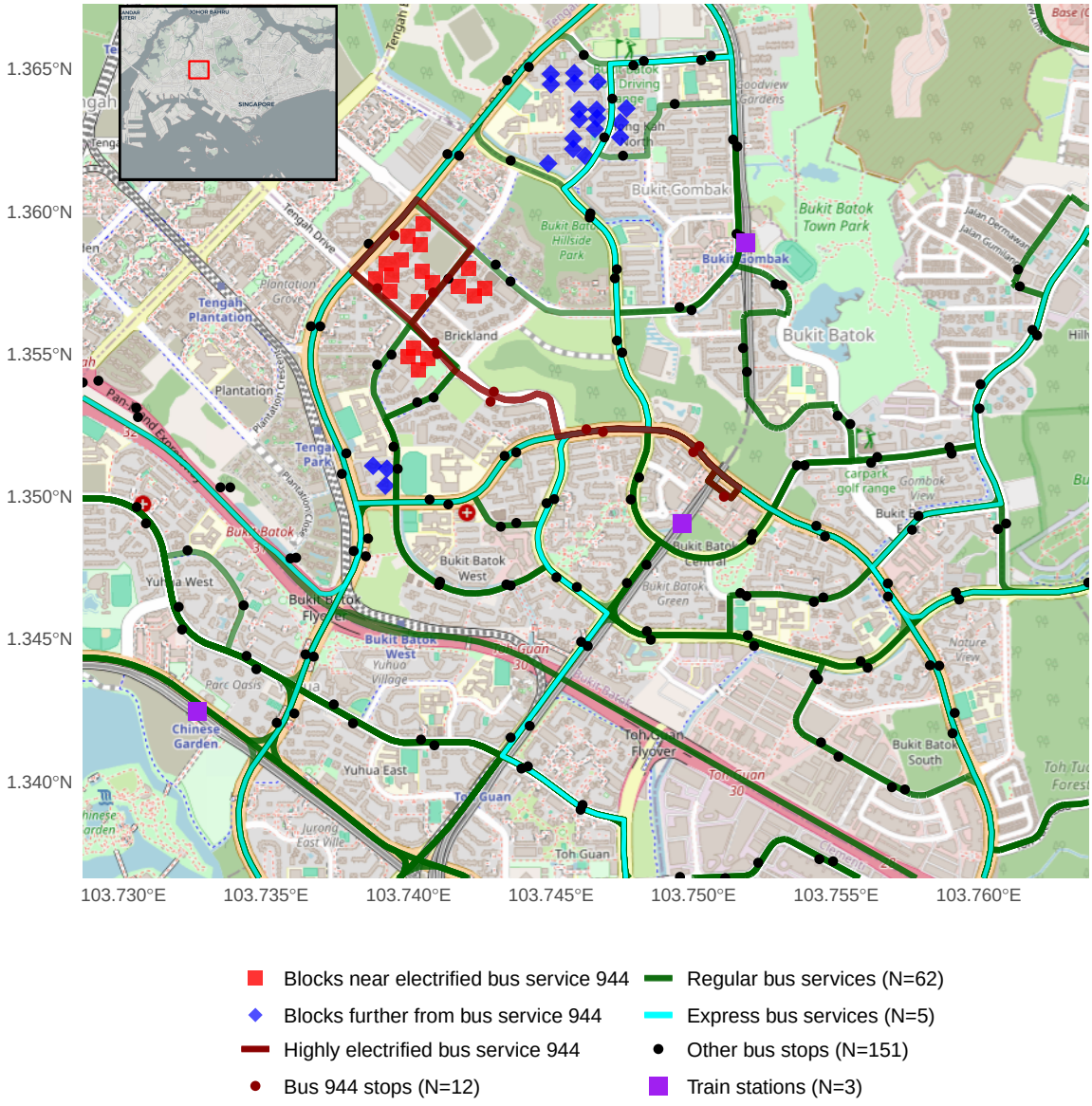
Notes: Ridership data spanning April 1, 2020 to March 31, 2022, aggregated to the participant-week level. An active week is a calendar week with at least one public-transport trip recorded to a participant's farecard. Relative to Table A12, we exclude three participants with only one active week and five with no trips prior to the baseline interview, leaving 580 participants. Rides paid with farecards retired before—or acquired after—baseline, or paid with bank cards, are not captured. The ridership data include farecard category (adult, senior citizen, disabled and workfare concession, pre-university student), which is broadly consistent with demographics collected directly from participants at baseline. Source: Land Transport Authority.

Table A14: Effect size of behavioral interventions on public transportation & sustainable mobility

Study	Domain	Intervention	Effect Size	Sample	Persistence
This Study	Cleaner buses (EV)	3-month video campaign on how citizens benefit from clean tech	+6 ppt use/+11 US cents ride^{-1}/+6 to +23% satisfaction	Singapore, 588-1200 households, low EV use	24 weeks after join panel study
Kristal and Whillans (2020)	Car-pooling	Letters/emails for carpooling, free bus trial, personalized travel plan	Zero	75K airport employees near a major European city	Not considered
Gravert and Collentine (2021)	Public transport	Social norms	Zero	Sweden, 14K individuals,	N/A
		Free PT pass extended 2 weeks	+50% trips in 8 months	72% use PT	7 months after 4-week trial
Enlund et al. (2023)	Multi-category incl. transport	Carbon calculators/ Mobile app	-8% transport carbon emissions	Sweden, 1240 individuals	Disappears after 10 weeks
Gessner et al. (2024)	Multi-modal transport	Social comparisons & moral appeals	Zero for PT, -10% car, +10% micro mobility	Germany, 341 employees	Disappears post-treatment
Hintermann et al. (2026)	Multi-modal transport	Pricing external damage	-5% external damage	Switzerland, 3616	Not considered
		Information only	-2% external damage	individuals	Not considered
Goetz et al. (2024)	Transport emissions	Gamification/ mobile app	-10% emissions	Switzerland, 410 individuals	Effects larger after 3-5 weeks

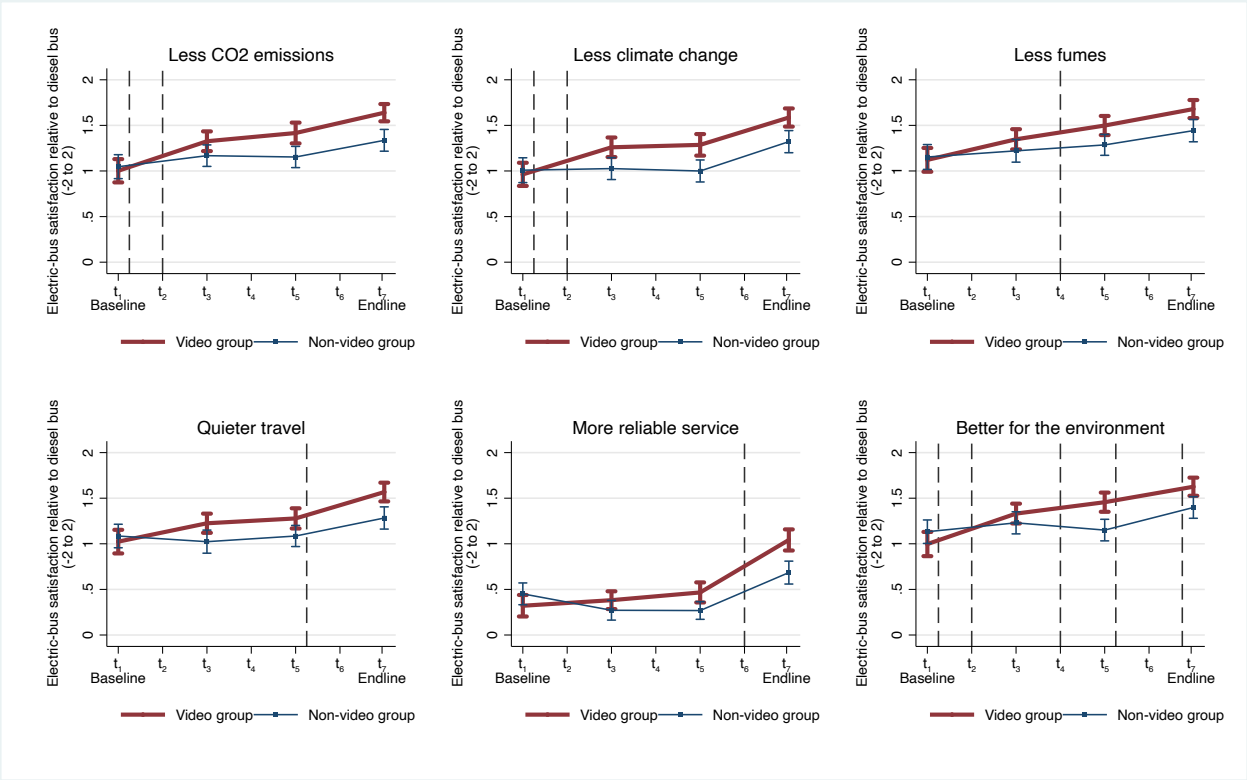
Notes: This table compares the estimated effect size with selected studies that use information intervention to promote sustainable transportation. PT = public transportation, EB = electric bus, K = thousands. If the average effect size is zero, persistence is reported as "N/A".

Figure A1: Spatial distribution of sampled residential blocks and public transport services in the intervention area



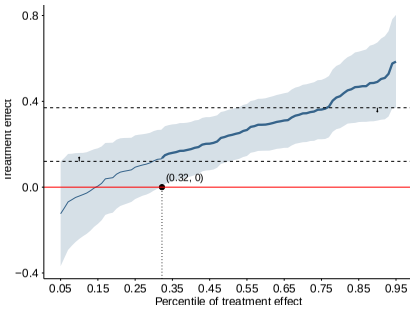
Notes: Locations of sampled residential blocks near (red squares) versus further from (blue diamonds) stops served by highly electrified bus service 944 (Figure A7), together with the route and stops of the 944, other bus services (62 regular services and five express services—174E, 188E, 868E, 963E, and 982E), and three nearby train stations (Bukit Batok, Bukit Gombak, and Chinese Garden) within a 1,500m buffer of the bus 944 route. The inset in the top-left corner situates the intervention area within Singapore.

Figure A2: Electric-bus satisfaction trends, by video treatment status

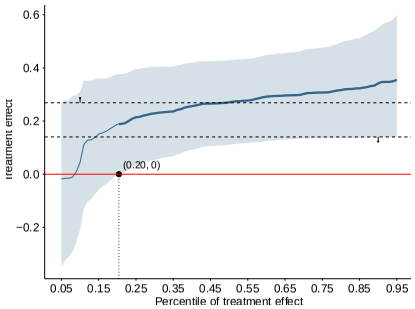


Notes: Electric-bus satisfaction trends over the course of the study for six co-benefits (relative to diesel buses): reduced carbon emissions, climate mitigation, less fumes, quieter travel, service reliability, and environmental impact. Scores are measured on a 5-point Likert scale and are coded as -2 (Diesel bus is better) through 0 (Same) to 2 (Electric bus is better). The horizontal axis denotes encounters, where t_1 is the baseline interview, t_2 is the first online round, and so forth. The thick red line represents mean scores for the video-treatment group and the thin blue line for the non-video group; whiskers denote the corresponding 95% confidence intervals. Vertical dashed lines mark encounters in which the video highlighted the corresponding topic to the video-treatment group. For example, videos comparing carbon emissions from electric and diesel buses were shown at the end of the baseline (and after the bus-type satisfaction question) and at the end of the first online encounter (no bus-type satisfaction question), thus vertical dashed lines are added just right of t_1 and of t_2. The sample includes 716 participants who completed all four encounters that asked bus-type satisfaction questions (t_1, t_3, t_5, t_7; Figure 1).

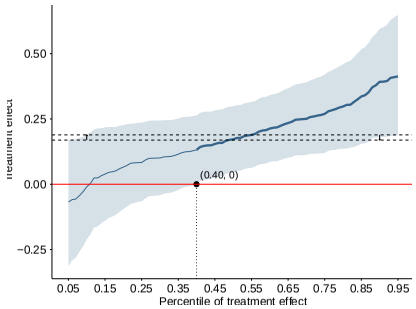
Figure A3: Electric-bus satisfaction: Treatment-effect heterogeneity



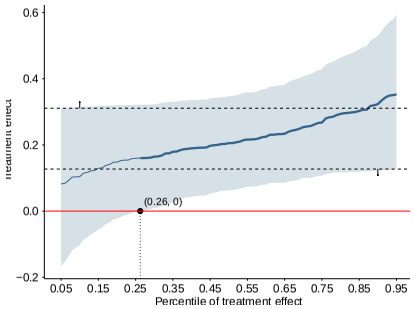
(**a**) Reduced carbon emissions



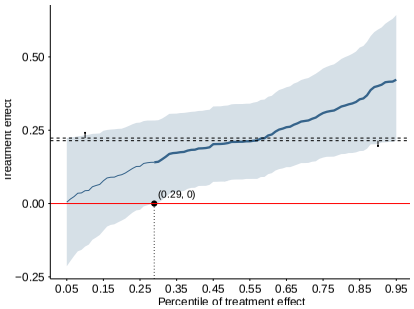
(**b**) Climate mitigation



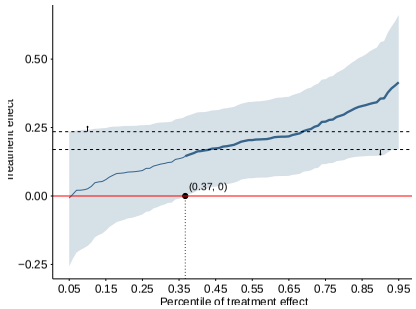
(**c**) Less fumes



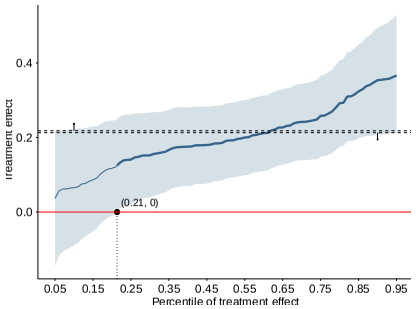
(**d**) Quieter travel



(**e**) Service reliability



(**f**) Better for the environment



(**g**) Electric-bus satisfaction index

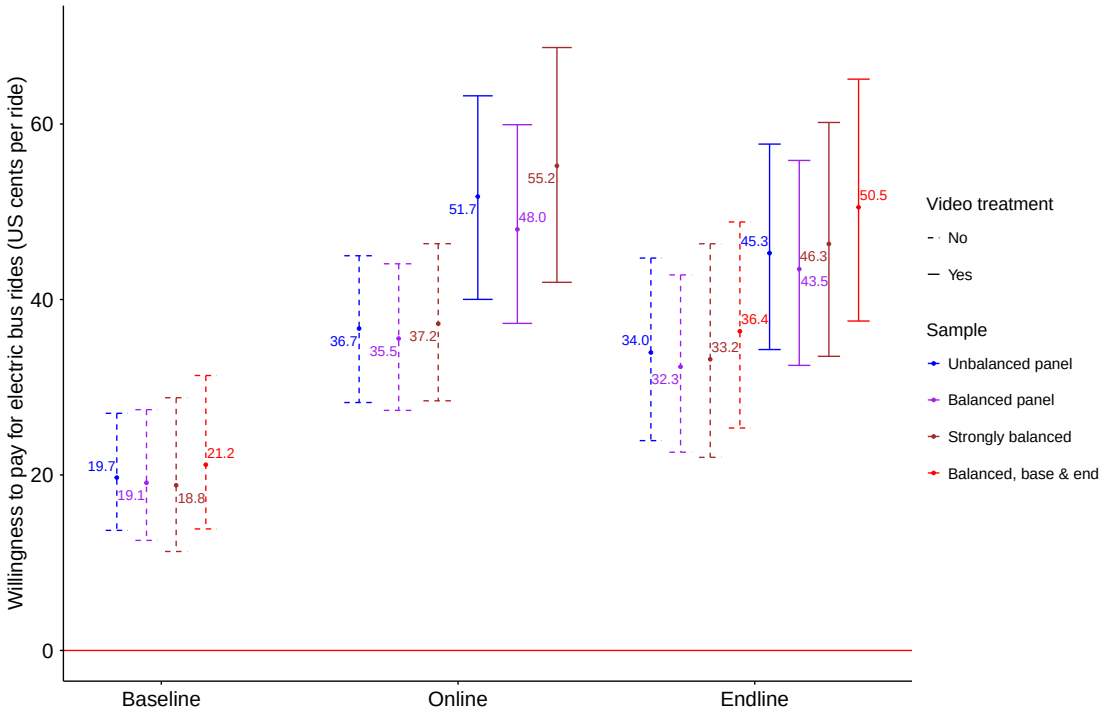
Notes: Treatment-effect heterogeneity in electric-bus satisfaction for six co-benefit dimensions, in panels a to f, and for the overall satisfaction index, in panel g, estimated using the Sorted Effects method (Chernozhukov et al., 2018). The estimation sample is that of Table 1. Continuous covariates are standardized using the baseline mean and standard deviation. The solid line plots the estimated sorted treatment-effect function $\Delta^{Y}_{\mu_Z}(u)$ across percentiles u, and the shaded area shows 95% uniform confidence bands computed from 5,000 bootstrap replications. Dashed horizontal lines mark the lower bound at the upper percentile ($u = 0.95$, downward arrow) and the upper bound at the lower percentile ($u = 0.05$, upward arrow), respectively; the null of no-treatment heterogeneity rejects at the 5% level in panels a and c. The marked point indicates the percentile at which the sorted treatment-effect function turns significantly positive at the 5% level; the thicker portion of the solid line shows the range of percentiles for which the estimated treatment effect is significantly positive.

Figure A4: Attribute manipulation for the value-of-time tasks

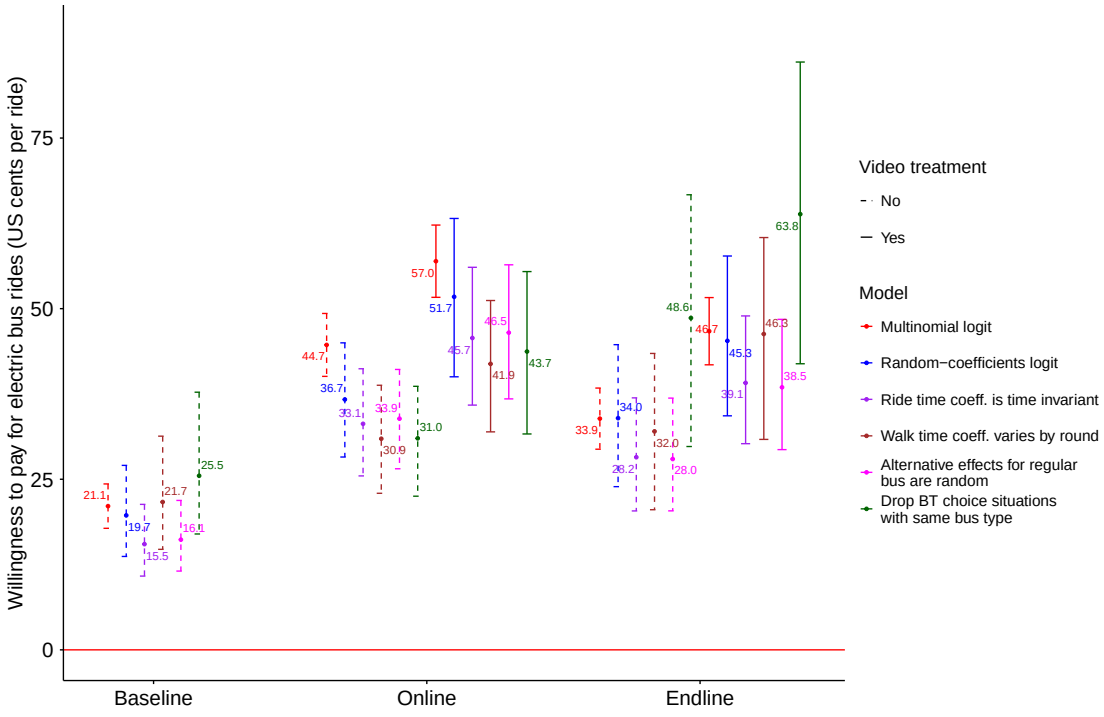
Ride time (min), Regular bus	Ride time (min), Express bus	Fare ($), Regular bus	Fare ($), Express bus
20	15	1.00	1.10
20	15	1.00	1.30
20	15	1.00	1.50
20	15	1.00	1.70
20	15	1.00	1.90
20	10	1.00	1.70
20	10	1.00	1.90
20	10	1.00	2.10
20	10	1.00	2.30
20	10	1.00	2.50
35	30	1.25	1.35
35	30	1.25	1.55
35	30	1.25	1.75
35	30	1.25	1.95
35	30	1.25	2.15
35	25	1.25	1.95
35	25	1.25	2.15
35	25	1.25	2.35
35	25	1.25	2.55
35	25	1.25	2.75
35	20	1.25	2.15
35	20	1.25	2.45
35	20	1.25	2.75
35	20	1.25	3.05
35	20	1.25	3.35
50	45	1.50	1.60
50	45	1.50	1.80
50	45	1.50	2.00
50	45	1.50	2.20
50	45	1.50	2.40
50	40	1.50	2.20
50	40	1.50	2.40
50	40	1.50	2.60
50	40	1.50	2.80
50	40	1.50	3.00
50	35	1.50	2.40
50	35	1.50	2.70
50	35	1.50	3.00
50	35	1.50	3.30
50	35	1.50	3.60

Notes: Combinations of attribute values in the value-of-time task. Each panel corresponds to a Regular bus ride time (20, 35, or 50 minutes) and fare ($1.00, $1.25, or $1.50) paired with an Express bus time saving (5, 10, or 15 minutes). Express fare premiums increase in $0.20 increments starting at $0.10 for 5-minute savings, in $0.20 increments starting at $0.70 for 10-minute savings, and in $0.30 increments starting at $0.90 for 15-minute savings. All amounts are in SG$.

Figure A5: WTP for electric bus by video treatment status: Robustness



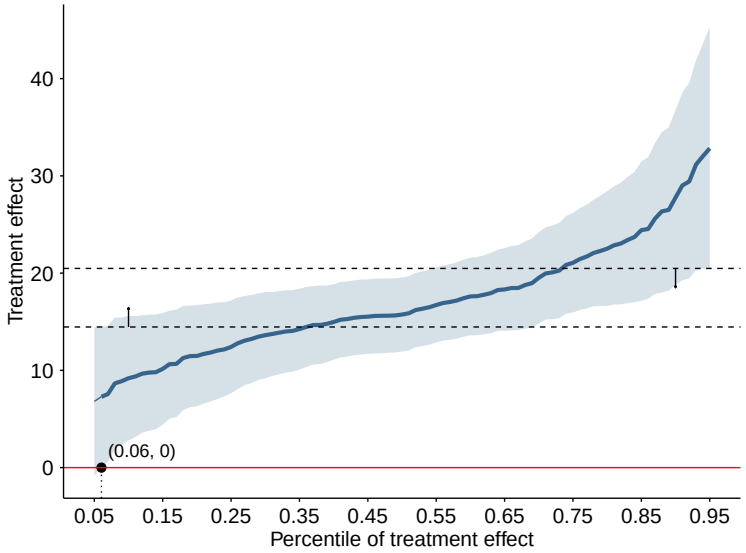
(**a**) Alternative samples



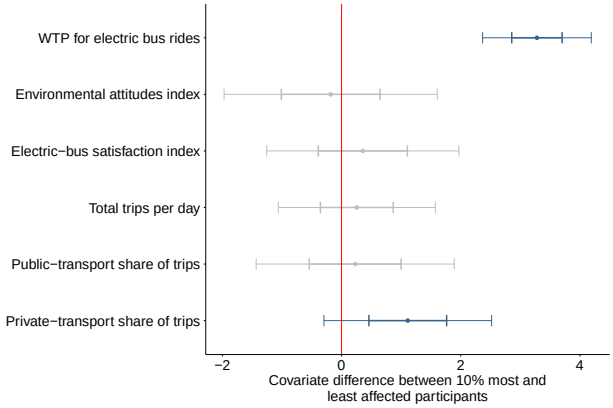
(**b**) Alternative specifications

Notes: Median WTP for electric bus rides across participants and random draws, based on the random-coefficients model estimates in Tables A8 and A9. Dashed and solid lines correspond to the non-video and video groups, respectively, with colors indicating the estimation sample (panel a) or the model specification (panel b) used. Dots indicate point estimates, and whiskers represent 95% confidence intervals computed using the Krinsky–Robb method.

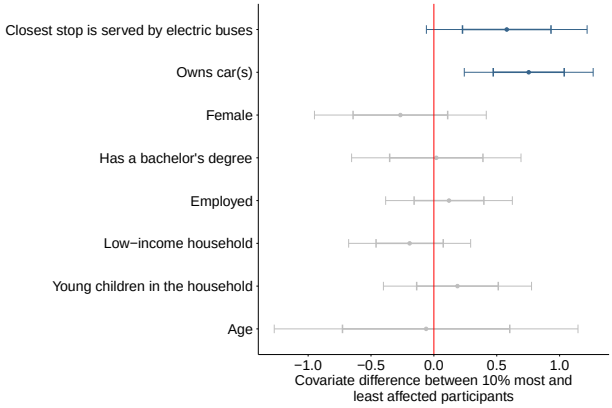
Figure A6: WTP for electric bus rides: Treatment-effect heterogeneity and characteristics of most- and least-affected participants



(**a**) Sorted treatment effects



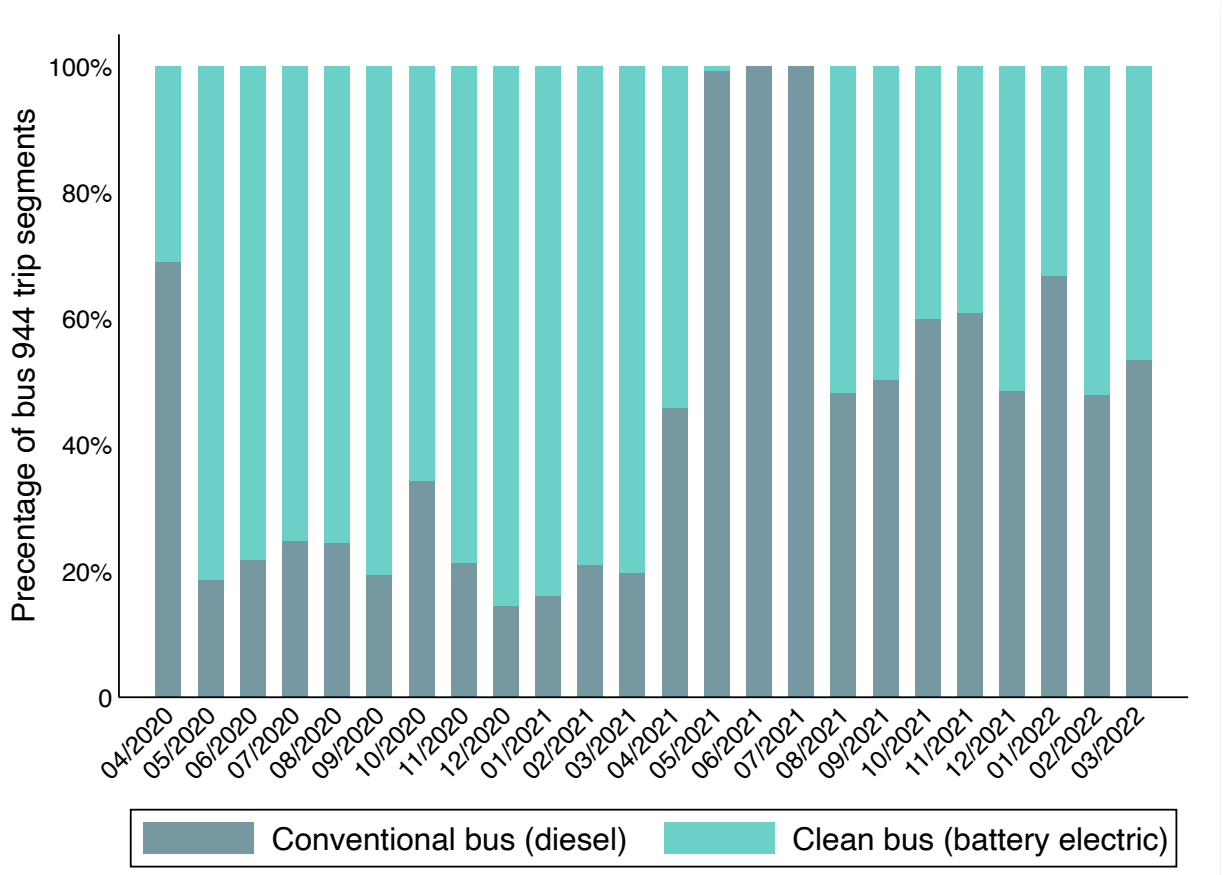
(**b**) Baseline outcomes



(**c**) Demographics

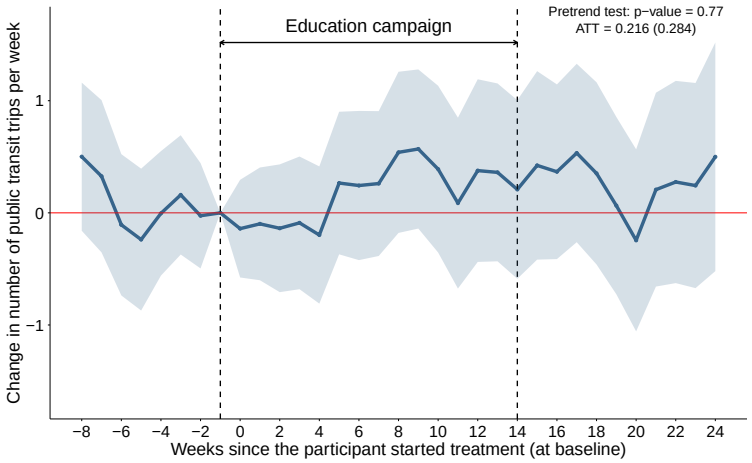
Notes: Panel a shows treatment-effect heterogeneity in WTP for electric bus rides, estimated using the Sorted Effects method (Chernozhukov et al., 2018). Continuous covariates are standardized using the baseline mean and standard deviation. The solid line plots the treatment-effect function $\Delta^{Y}_{\mu_Z}(u)$ across percentiles u, and the shaded area shows 95% uniform confidence bands. Dashed horizontal lines mark the lower bound at the upper percentile ($u = 0.95$, downward arrow) and the upper bound at the lower percentile ($u = 0.05$, upward arrow), respectively; the null of no-treatment heterogeneity rejects at the 5% level, because the dashed line at $u = 0.05$ lies below the dashed line at $u = 0.95$. The marked point indicates the percentile at which the treatment-effect function turns significantly positive at the 5% level; the thicker portion of the solid line shows the range of percentiles for which the estimated treatment effect is significantly positive. Panels b and c show covariate differences between the top and bottom deciles of treatment effects on WTP for electric bus rides for baseline outcomes and demographic covariates, respectively. Dots indicate point estimates; narrow bars show independent 95% confidence bands, while wider bars show uniform confidence intervals adjusted for the family-wise error rate within each covariate family. Significant positive (negative) differences at the 5% level are labeled in blue (red), while insignificant differences are labeled in gray. Confidence intervals computed from 5,000 bootstrap replications.

Figure A7: Share of bus service 944's trip segments that are electric vs. diesel

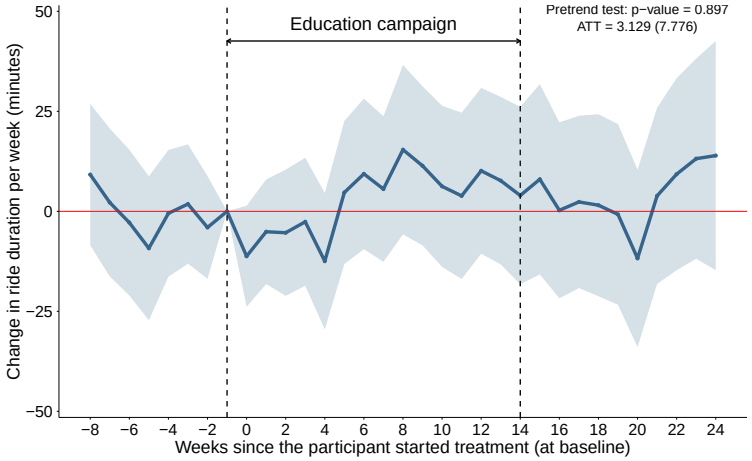


Notes: Electric vs. diesel shares of bus service 944 segments in the ridership data. Service 944 is a local feeder linking residential blocks to Bukit Batok town centre, which hosts three malls and the bus and train interchange for onward journeys (Figure A1). Half of the participants had service 944 stopping in front of their housing block. Source: Public-transport ridership data.

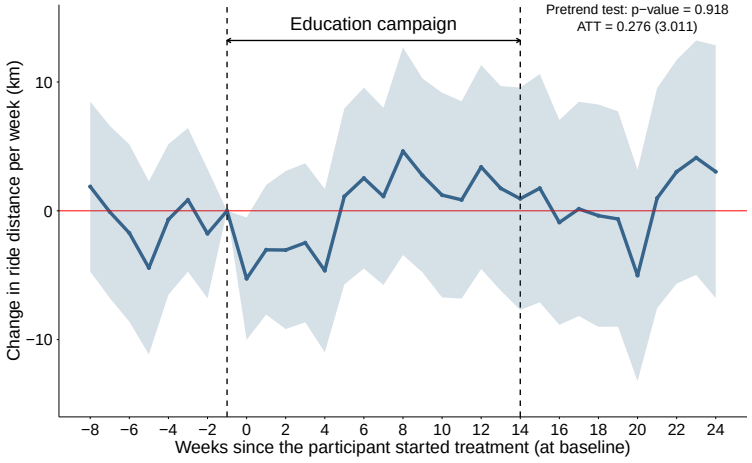
Figure A8: Event study of the video treatment effect on public transport usage



(**a**) Weekly number of public-transport trips



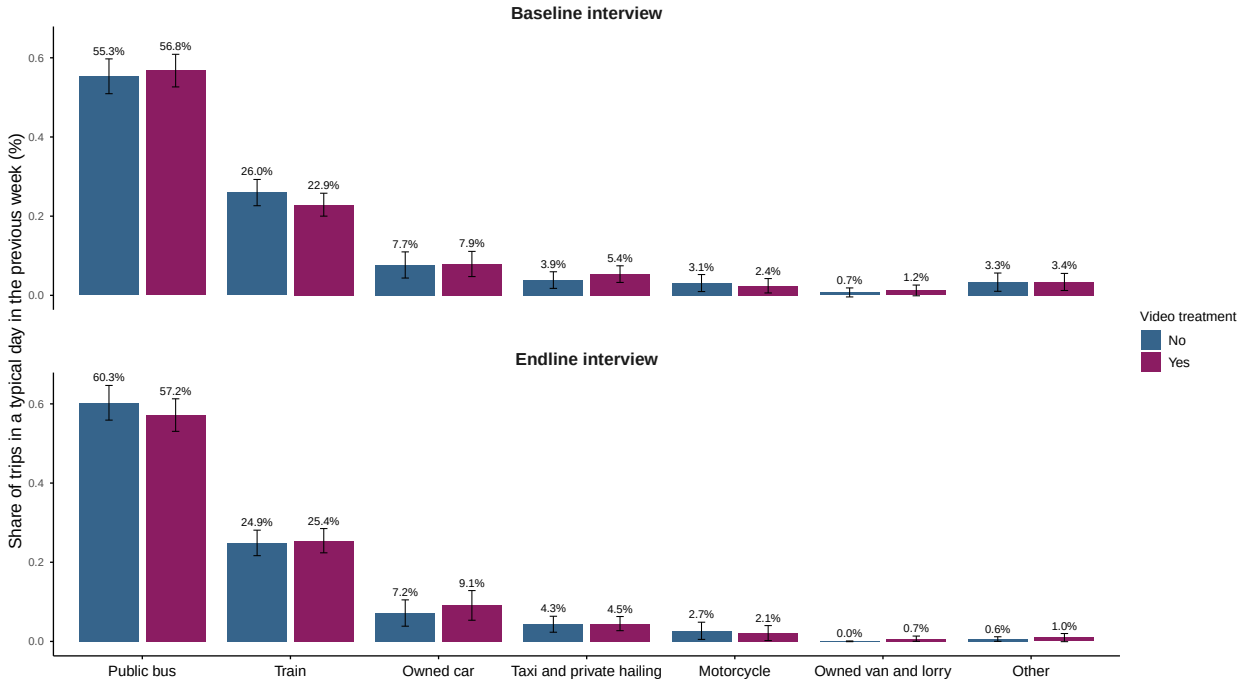
(**b**) Weekly ride duration



(**c**) Weekly distance traveled

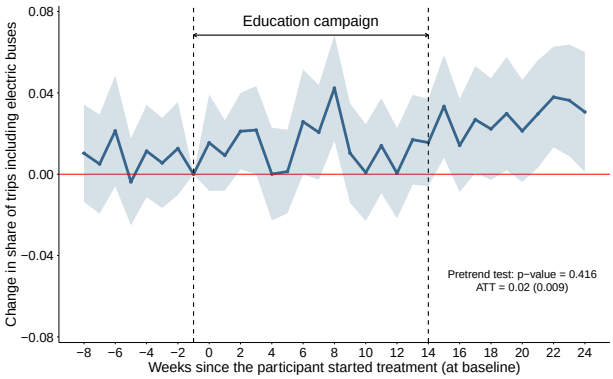
Notes: Event study estimates of the video treatment effect on the weekly number of public-transport trips, total ride duration (minutes), and distance traveled (kilometers), using the Callaway and Sant'Anna (2021) estimator. Other notes in the caption to Figure 7 apply here.

Figure A9: Self-reported travel mode at baseline and endline by video treatment status

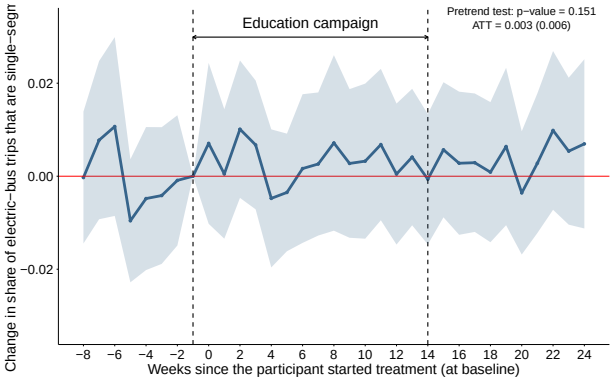


Notes: Self-reported trips by motorized travel mode on a typical day in the past week, at baseline before treatment began (top panel) and endline (bottom panel), for the video treatment (right bar within mode) and non-video (left bar) groups. Shares are weighted by self-reported travel days in the week, to emphasize frequent travelers (Appendix A.1). To align with Section 5.2, we restrict the sample to the 580 participants who provided farecard numbers with active travel at baseline (Tables A10 and A13); findings are similar for the 996 participants who completed the endline. Bar heights are point estimates; whiskers denote 95% confidence intervals.

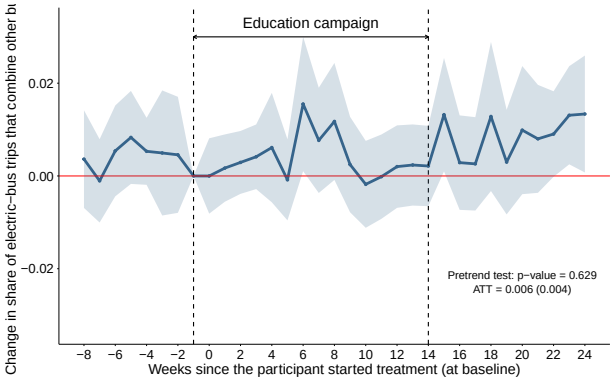
Figure A10: Event study of the video treatment effect on electric-bus segment shares



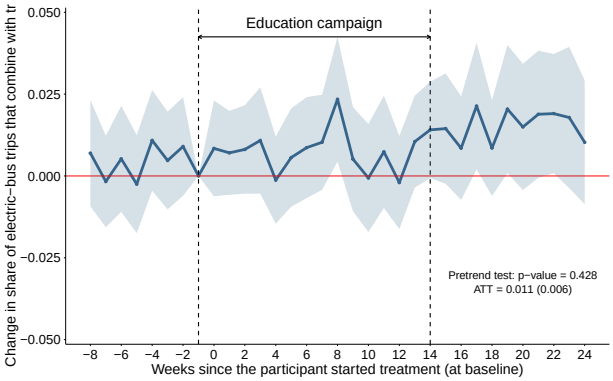
(**a**) Share of trips that include an electric-bus segment



(**b**) Share of electric-bus trips that are single-segment



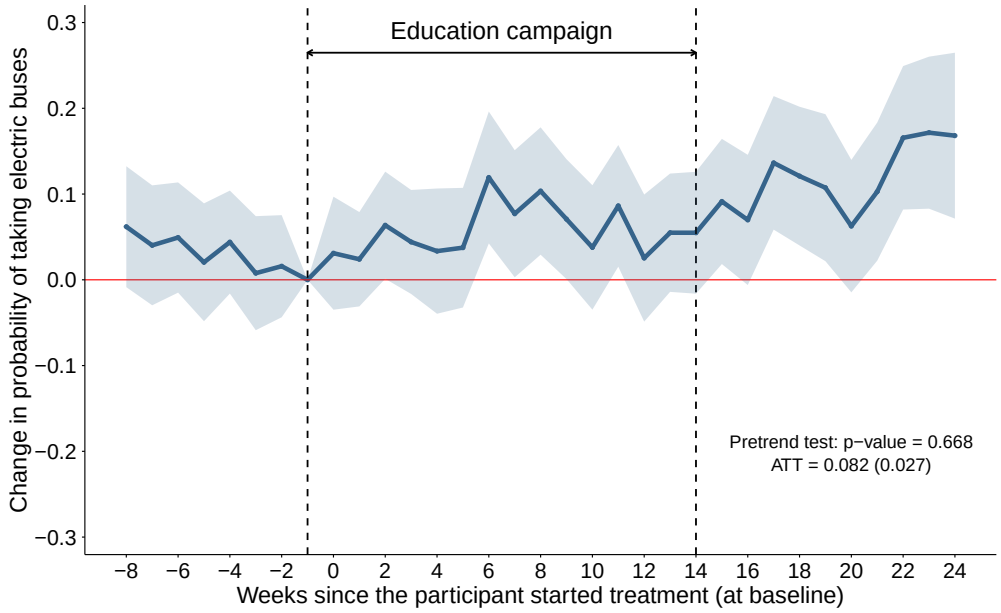
(**c**) Share of electr.-bus trips that combine other buses



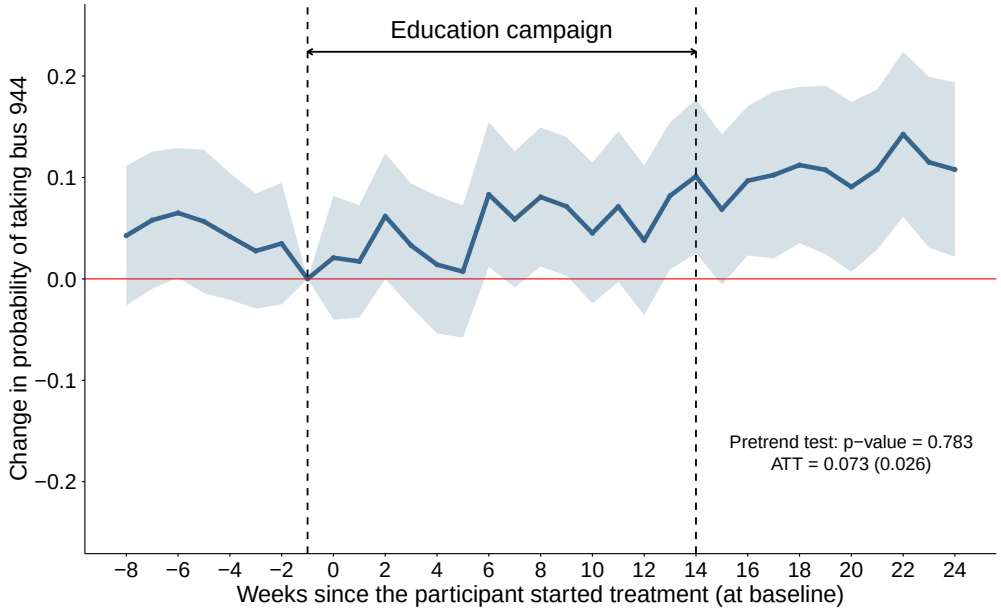
(**d**) Share of electric-bus trips that combine with trains

Notes: Event study estimates of the video treatment effect using the Callaway and Sant'Anna (2021) estimator, on the share (a) of trips that include an electric-bus segment, (b) of electric-bus trips that are single-segment, (c) of trips that combine electric buses with other bus services, and (d) of trips that combine electric buses with trains. Here, we restrict the sample to trips with at least one segment starting and arriving within 1,500m of bus 944 stops (these account for 52% of trips in the farecard data, i.e., over half of the segments in the sample are quite local). Other notes in the caption to Figure 7 apply here.

Figure A11: Event study of the video treatment effect on the probability of riding electric buses: Robustness to restricting sample to weeks of active farecard use



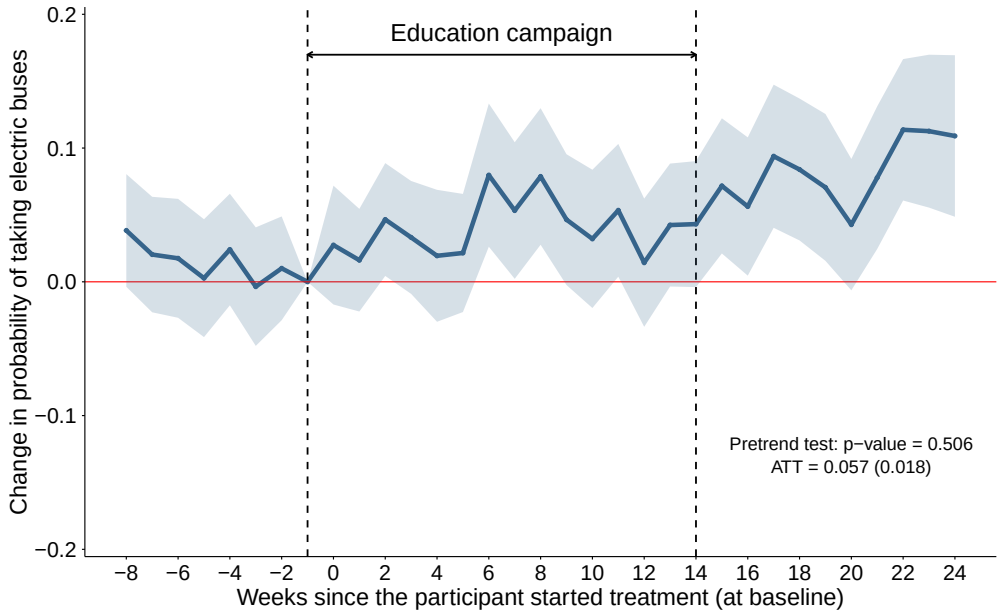
(**a**) Probability of riding electric buses (any service)



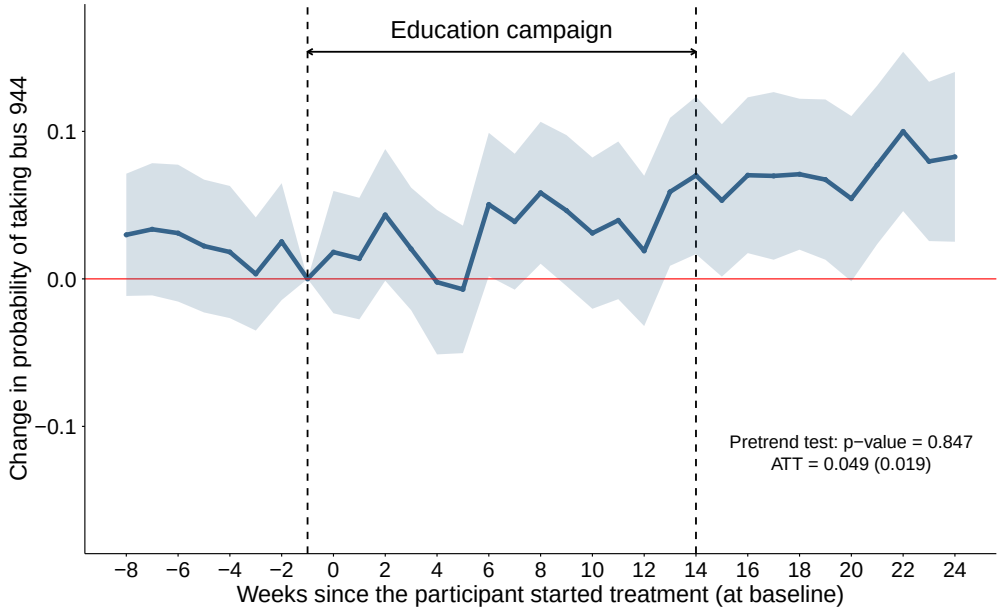
(**b**) Probability of riding bus highly electrified service 944

Notes: Event study estimates of the video treatment effect on the probability of riding electric buses (any service; panel a) or the highly electrified bus service 944 (panel b), using the Callaway and Sant'Anna (2021) estimator. The sample (now unbalanced) is restricted to participant-weeks with at least one farecard trip. Other notes in the caption to Figure 7 apply here.

Figure A12: Event study of the video treatment effect on the probability of riding electric buses: Robustness to specifying not-yet-treated units as the comparison group



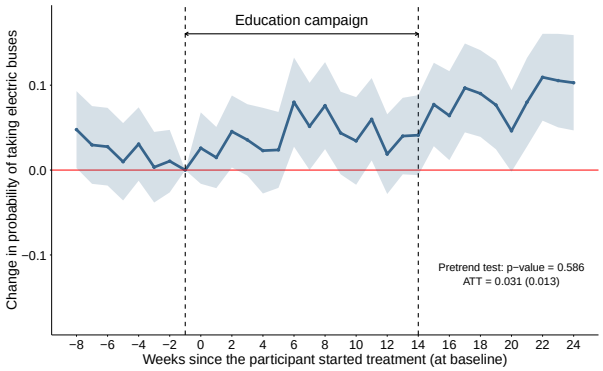
(**a**) Probability of riding electric buses (any service)



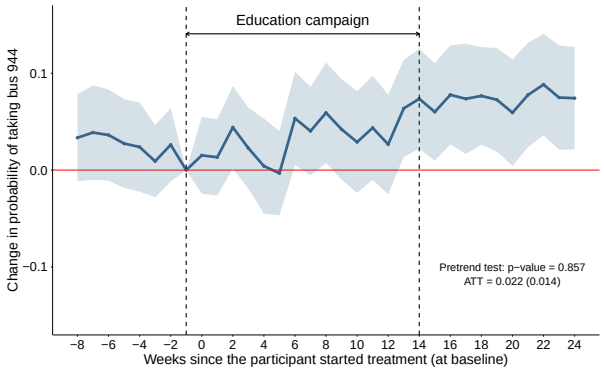
(**b**) Probability of riding bus highly electrified service 944

Notes: Event study estimates of the video treatment effect on the probability of riding electric buses (any service; panel a) or the highly electrified bus service 944 (panel b), using the Callaway and Sant'Anna (2021) estimator. The comparison group consists of not-yet-treated units—all non-video group and pre-baseline video group observations—rather than never-treated units. Other notes in the caption to Figure 7 apply here.

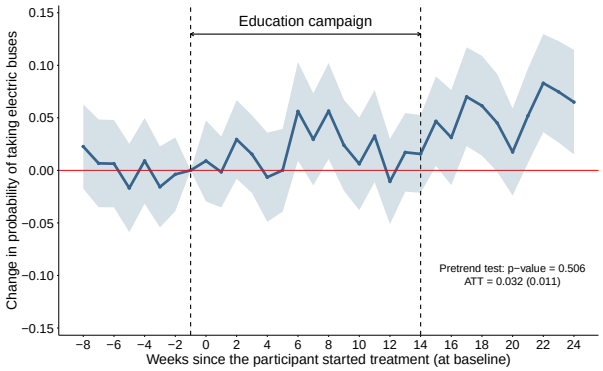
Figure A13: Event study of the video treatment effect on the probability of riding electric buses: Robustness to other DiD estimators



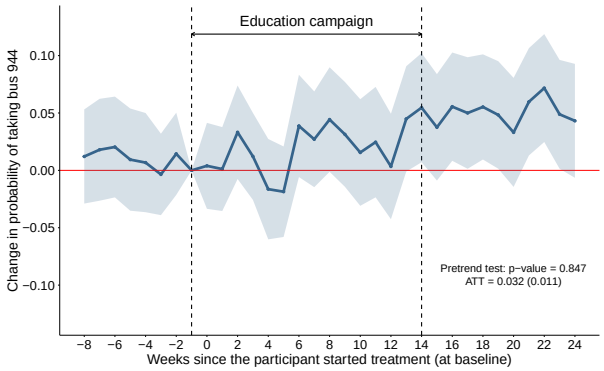
(**a**) TWFE: Prob. riding electric buses



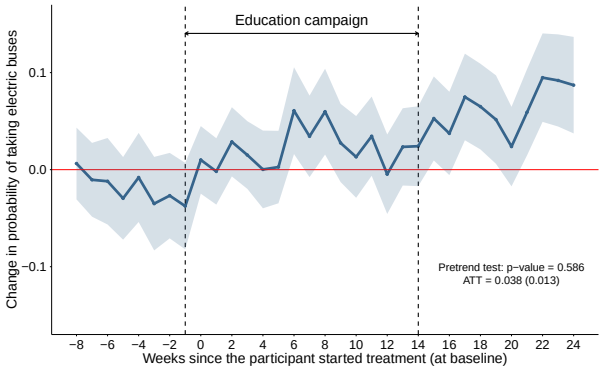
(**b**) TWFE: Prob. riding service 944



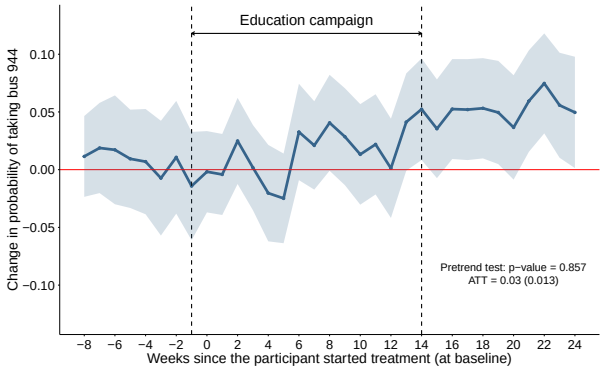
(**c**) R-SA: Prob. riding electric buses



(**d**) R-SA: Prob. riding service 944



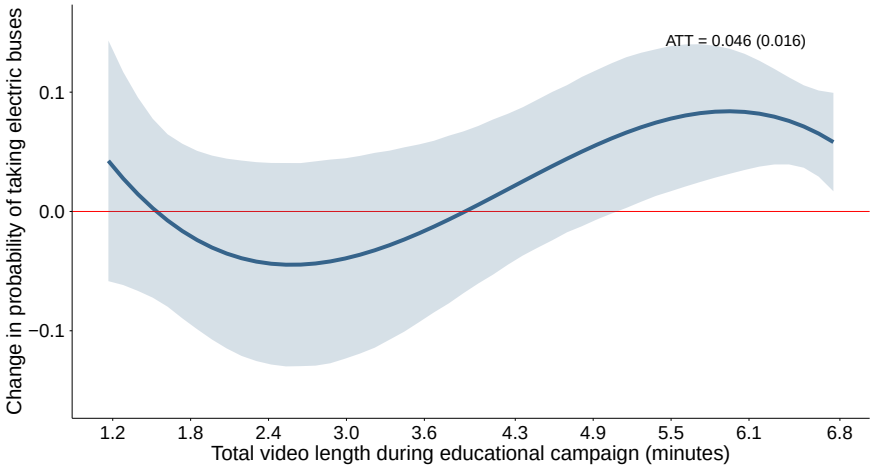
(**e**) BJS: Prob. riding electric buses



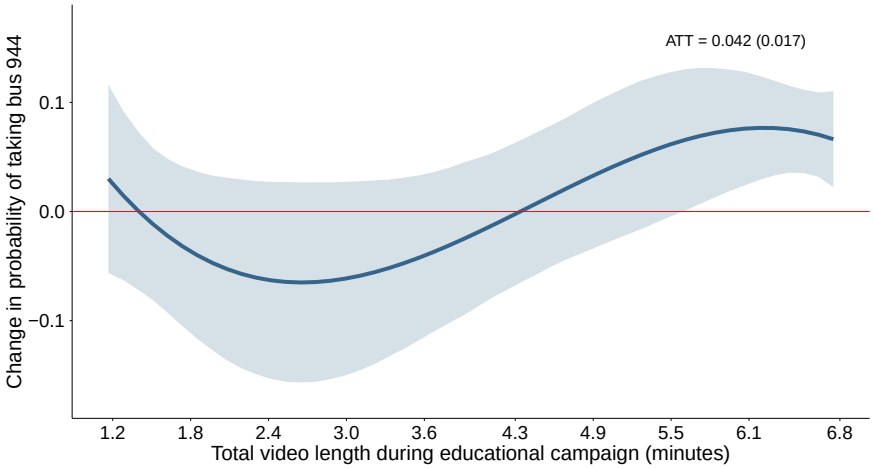
(**f**) BJS: Prob. riding service 944

Notes: Event study estimates of the video treatment effect on the probability of riding electric buses (any service; left panels) or the highly electrified bus service 944 (right panels), using the two-way fixed effect estimator (TWFE; top row), the efficient plug-in estimator for staggered rollout design (R-SA; middle row) (Roth and Sant'Anna, 2023), and the imputation estimator (BJS; bottom row) (Borusyak et al., 2024). Other notes in the caption to Figure 7 apply here.

Figure A14: Continuous treatment effect on the probability of riding electric buses



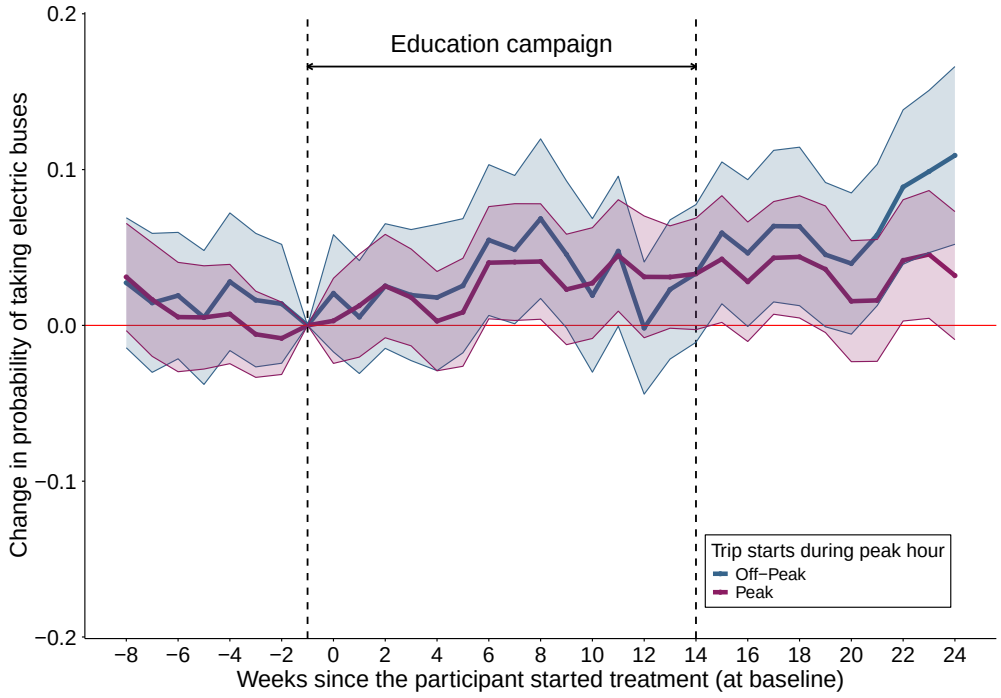
(**a**) Probability of riding electric buses (any service)



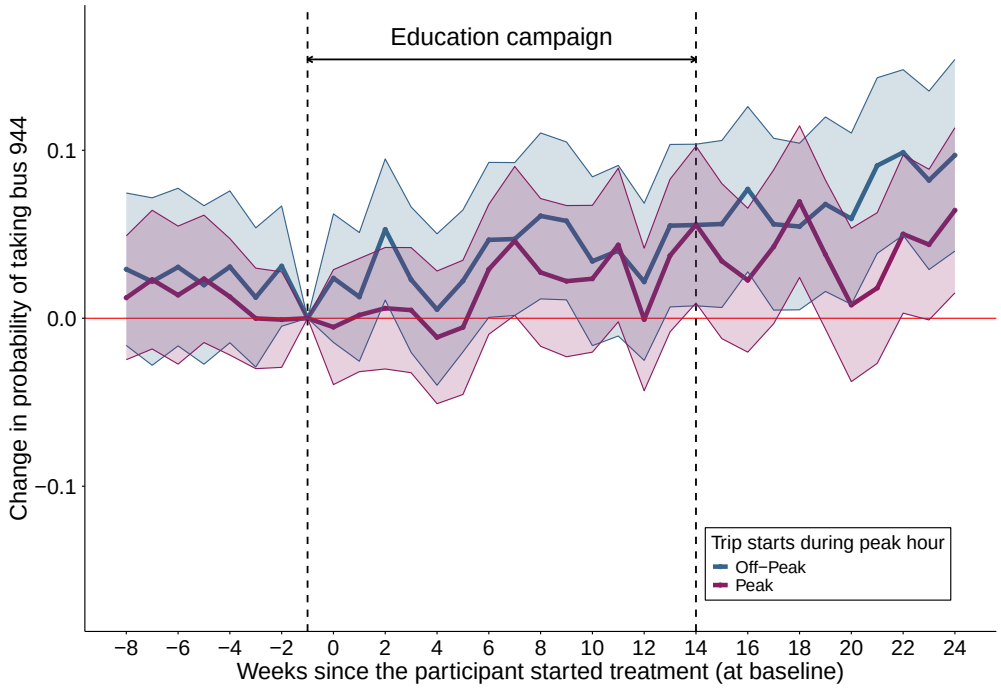
(**b**) Probability of riding bus highly electrified service 944

Notes: ATT estimates of the video treatment effect on the probability of riding electric buses (any service; panel a) or the highly electrified bus service 944 (panel b) as a function of total video-education minutes received. We use the continuous DiD estimator of Callaway et al. (2025) with a cubic polynomial fit, collapsing participant-level trips to to two periods: pre-baseline and post-endline. The solid line shows point estimates; the shaded region is 95% level uniform confidence band.

Figure A15: Event study of the video treatment effect on the probability of riding electric buses: Peak versus non-peak hours



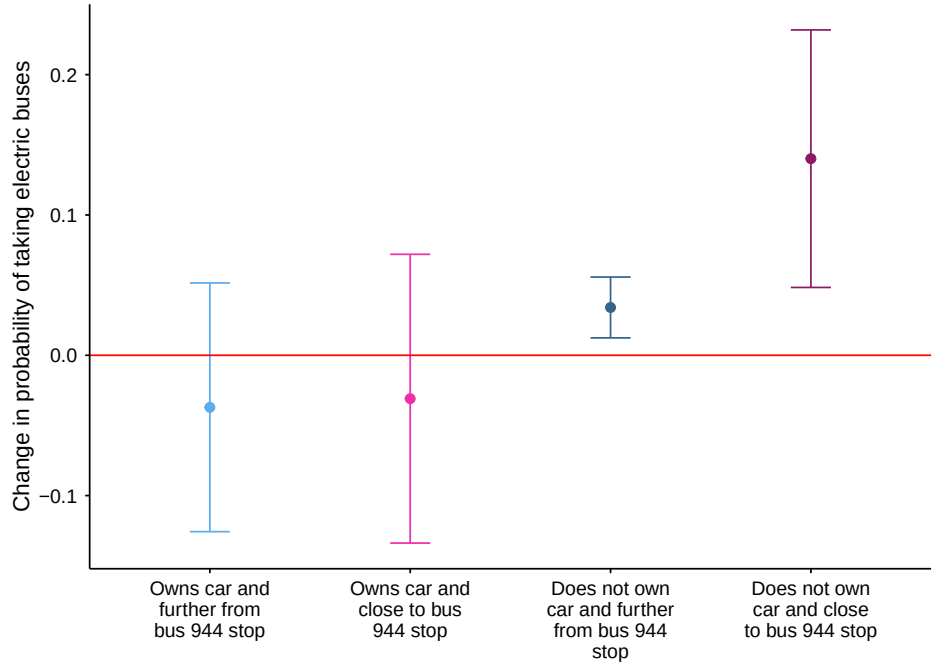
(**a**) Probability of riding electric buses (any service)



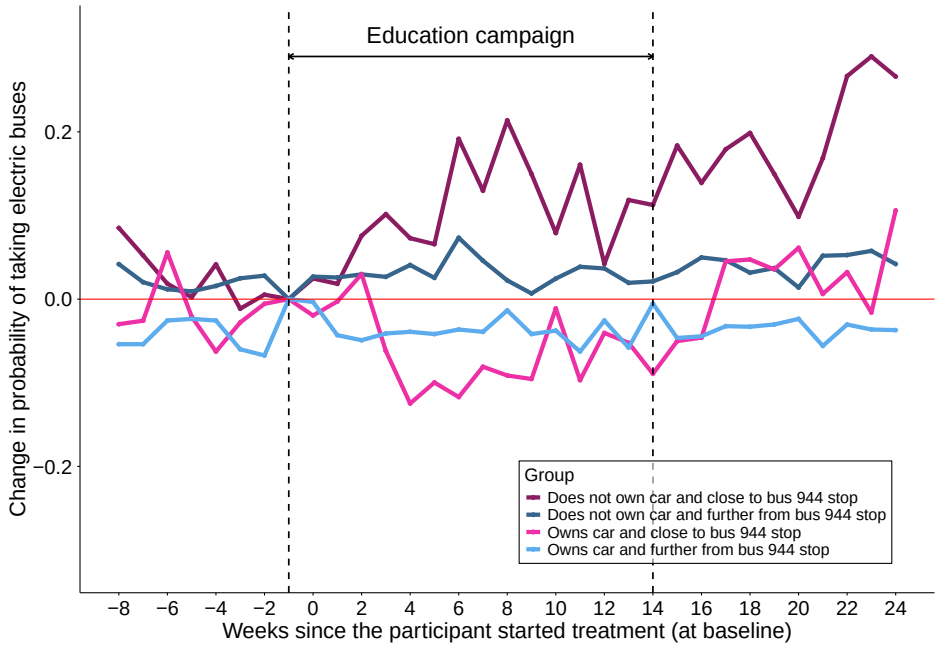
(**b**) Probability of riding bus highly electrified service 944

Notes: Event study estimates of the video treatment effect on the probability of riding electric buses (any service; panel a) or the highly electrified bus service 944 (panel b), using the Callaway and Sant'Anna (2021) estimator, on two subsamples: trips starting during workday peak hours (red) or outside of them (blue). Other notes in the caption to Figure 7 apply here.

Figure A16: Heterogeneous impact of video treatment on the probability of riding electric buses, by car ownership and proximity to bus 944 stops



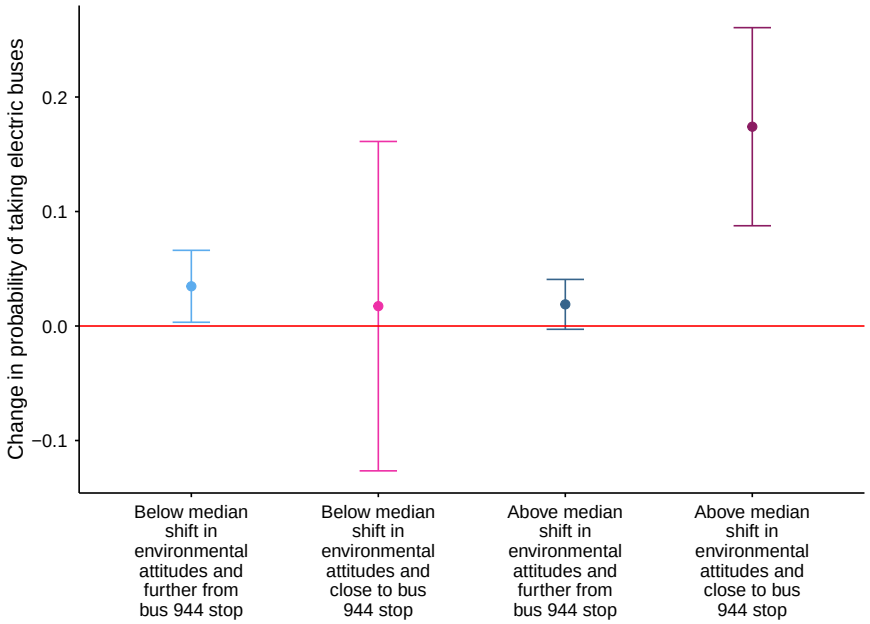
(**a**) Static estimates



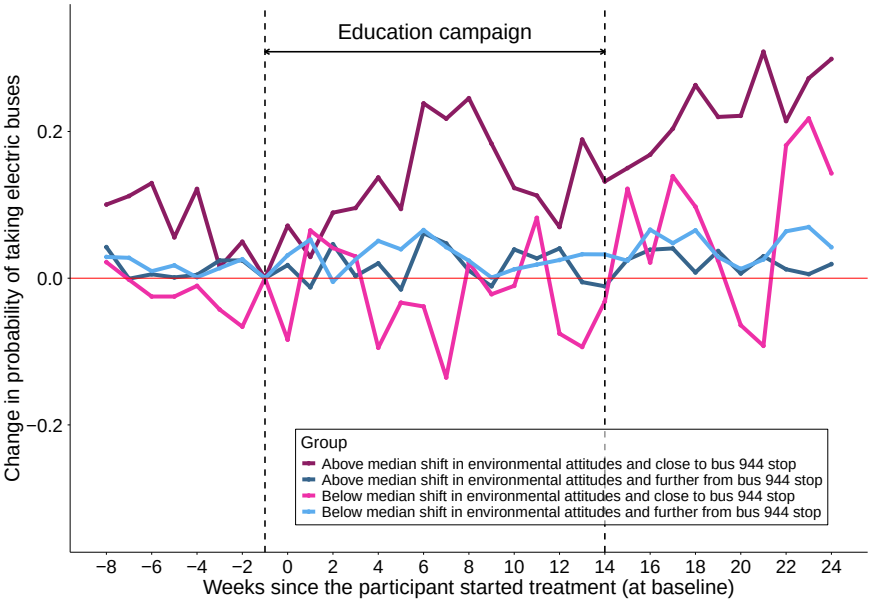
(**b**) Event study estimates

Notes: Static (panel a) and event study (panel b) estimates of the video treatment effect on the probability of riding electric buses (any service), using the Callaway and Sant'Anna (2021) estimator applied separately to subsamples defined by household car ownership and proximity to stops served by the highly electrified service 944. Panel a shows point estimates with 95% confidence intervals; panel b plots point estimates only for clarity. Subgroup sample sizes: $N = 194$ (no car, near 944 stop), $N = 232$ (no car, further from 944 stop), $N = 76$ (car, near 944 stop), $N = 78$ (car, further from 944 stop).

Figure A17: Heterogeneous impact of video treatment on the probability of riding electric buses, by shift in environmental attitudes and proximity to bus 944 stops



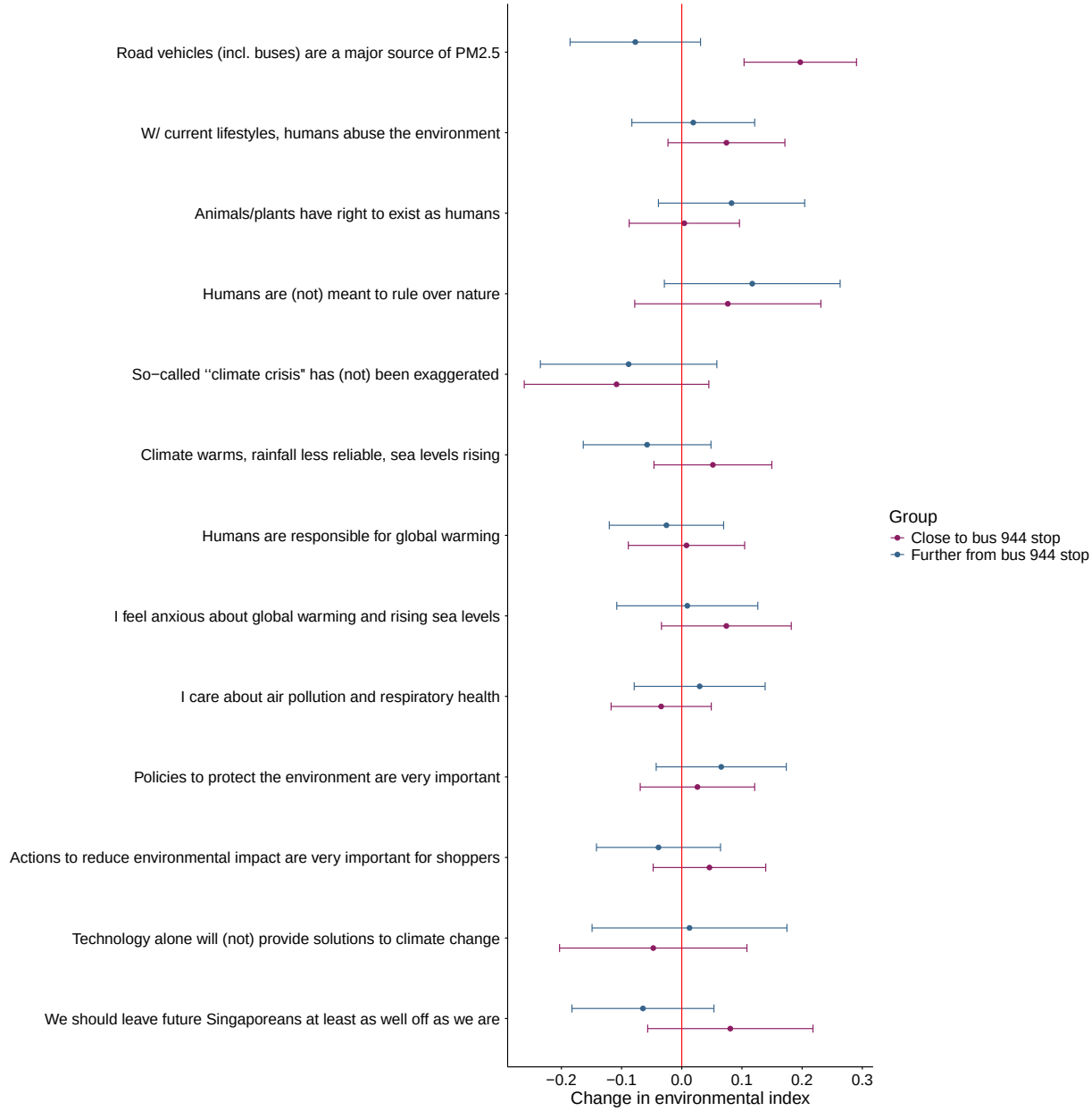
(**a**) Static estimates



(**b**) Event study estimates

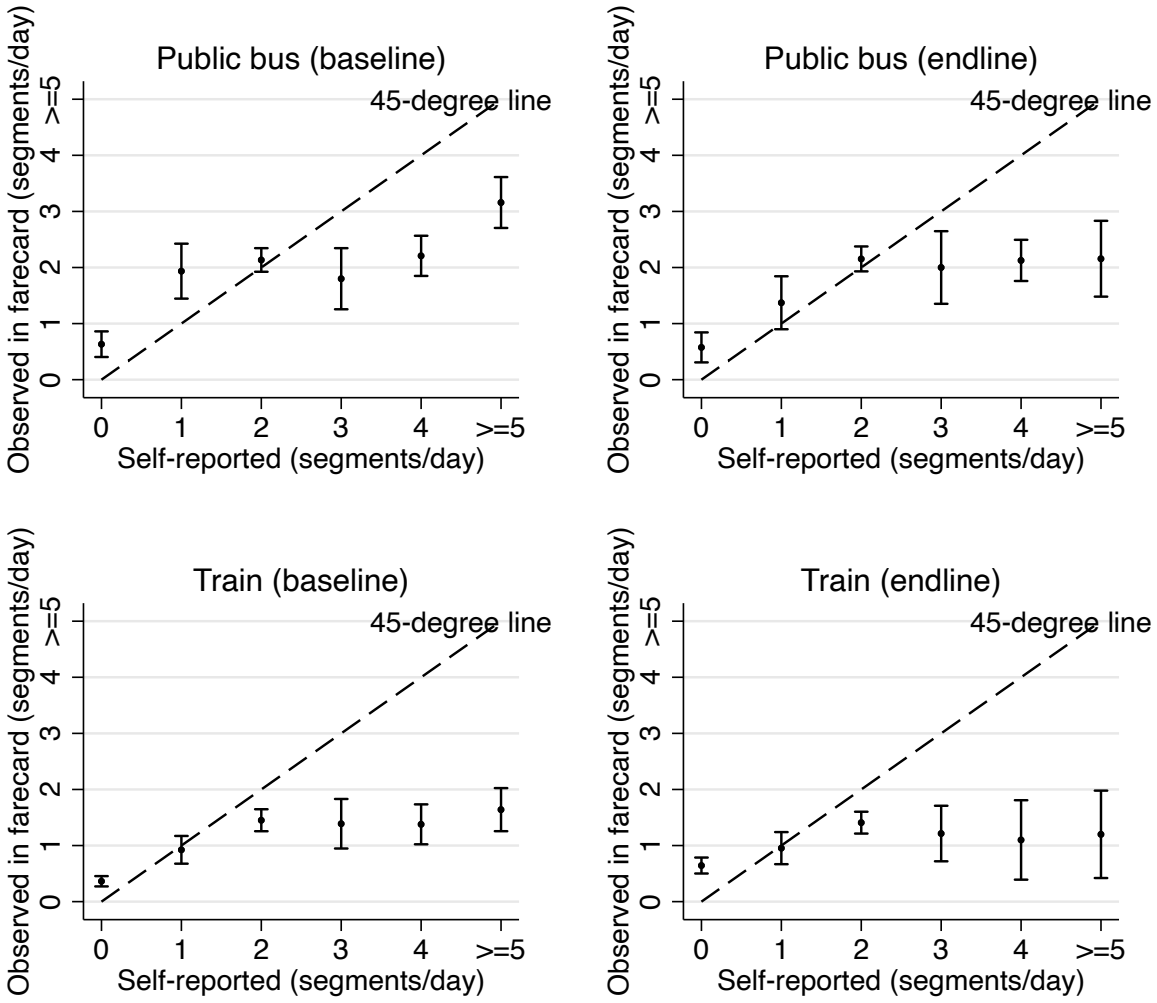
Notes: Static (panel a) and event study (panel b) estimates of the video treatment effect on the probability of riding electric buses (any service), applied separately to subsamples defined by the baseline-to-endline change in environmental attitudes and proximity to stops served by the highly electrified service 944. Panel a shows point estimates with 95% confidence intervals; panel b plots point estimates only for clarity. The sample consists of 481 participants who provided farecard numbers and completed the endline interview. Subgroup sample sizes: $N = 135$ (above-median change, near 944 stop), $N = 106$ (above-median change, further from 944 stop), $N = 88$ (below-median shift, near 944 stop), $N = 152$ (below-median shift, further from 944 stop).

Figure A18: Video treatment effect on environmental attitudes, itemized



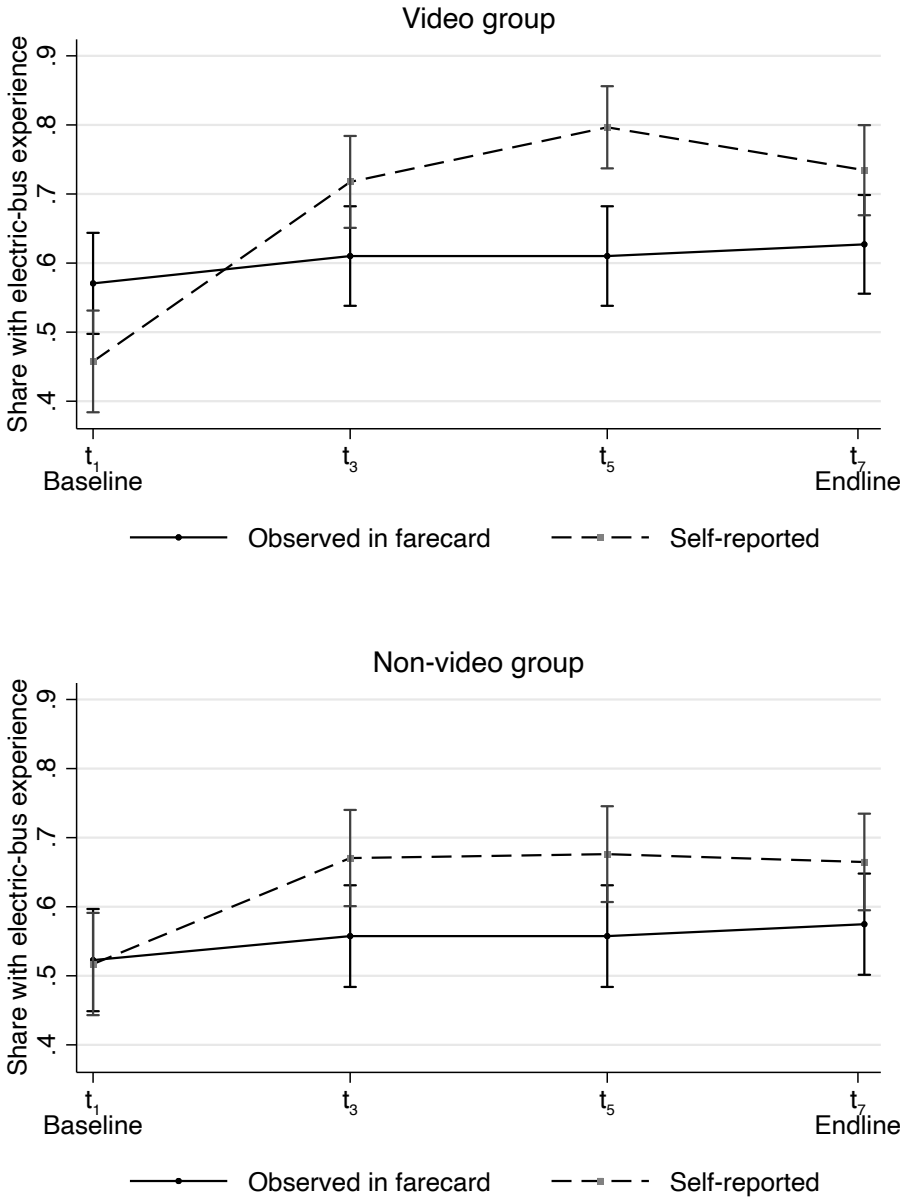
Notes: Estimates of the video treatment effect on each of 13 statements spanning environmental stewardship, climate anxiety, intergenerational equity, and the role of individual action (Table A3), by distance to electrified bus service 944 stops, using equation 3 (interaction of treatment indicator and participant characteristics). The regression sample includes baseline and endline responses of 996 participants who completed both interviews. Dots are point estimates; whiskers are 95% confidence intervals.

Figure A19: Public-transport trip segments: Observed in farecards vs. self-reported



Notes: Binscatter plots comparing actual and self-reported travel on public buses (top panels) and trains (bottom panels) in the one week preceding a participant's baseline interview (left panels) and endline interview (right panels). Actual trip segments are measured as the maximum daily count recorded in the week preceding each interview (Appendix A.6). Rides a participant paid with farecards other than those whose number was shared at baseline, or paid with bank cards, are not captured. Black dots represent the mean number of actual trip segments at each self-reported level (Appendix A.1); whiskers indicate 95% confidence intervals computed using the method of Cattaneo et al. (2024).

Figure A20: Electric-bus experience: Observed in farecards vs. self-reported



Notes: Actual versus self-reported electric-bus experience for the video treatment group (top panel) and non-video group (bottom panel). The actual share is the proportion of participants with electric-bus trips recorded in farecard data prior to each encounter in which experience was surveyed—baseline (t_1), second online (t_3), fourth online (t_5), and endline (t_7) (Appendix A.3). This plot is based on a balanced panel of 353 participants who provided a farecard number and completed all four of these encounters. Rides a participant paid with farecards other than those whose number was shared at baseline, or paid with bank cards, are not captured. Whiskers represent 95% confidence intervals.