HIAS-E-115

Do Economic Incentives Promote Physical Activity?

Evidence from the London Congestion Charge

Ryota Nakamura [(a)], Andrea Albanese [(b)], Emma Coombes [(c)], Marc Suhrcke [(b) (d)]

(a) Hitotsubashi Institute for Advanced Study, Hitotsubashi University
(b) Luxembourg Institute of Socio-Economic Research
(c) University of East Anglia
(d) University of York

December, 2021

Hitotsubashi Institute for Advanced Study, Hitotsubashi University
2-1, Naka, Kunitachi, Tokyo 186-8601, Japan
tel:+81 42 580 8668 http://hias.hit-u.ac.jp/

Do Economic Incentives Promote Physical Activity? Evidence from the London Congestion Charge*

Ryota Nakamura[a], Andrea Albanese[b], Emma Coombes[c], Marc Suhrcke[b,d]

This version: December 2021

Abstract

This study investigates the impact of economic incentives on travel-related physical activity, leveraging the London Congestion Charge's disincentivising of sedentary travel modes via increasing the cost of private car use within Central London. The scheme imposes charges on most types of cars entering, exiting and operating within the Central London area, while individuals living inside the charging zone are eligible for a 90% reduction in congestion charges. Geographical location information provides the full-digit postcode data necessary to precisely identify the eligibility for the discount of participants in the London Travel Demand Survey for the period 2005–2011. Using a boundary regression-discontinuity design reveals a statistically significant but small impact on active commuting (i.e. cycling and walking) around the border of the charging zone. The effect is larger for lower-income households and car owners. The findings are robust against multiple specifications and validation tests.

Keywords: economic incentive; health behaviour; London Congestion Charge; geographical information system; regression-discontinuity.

JEL Classification Codes: D04, I12, R48

---

* This study was funded by the UKCRC Centre for Diet and Physical Activity Research (CEDAR). The funders had no role in the study design, data collection, analysis or interpretation.

[a] *Corresponding author*: Hitotsubashi Institute for Advanced Study, Hitotsubashi University. Email: ryota.nakamura@r.hit-u.ac.jp

[b] Luxembourg Institute of Socio-Economic Research.

[c] Norwich Medical School, University of East Anglia.

[d] Centre for Health Economics, University of York.

1. Introduction

Economic incentives, especially when established through large-scale fiscal policies, have long been considered an effective economic tool for reducing unhealthy behaviours such as smoking, alcohol consumption and unhealthy diet (Gruber and Koszegi, 2001; Yaniv et al., 2009; Volpp et al., 2009; Giné et al., 2010; Cawley and Ruhm, 2011; Cawley et al., 2019). However, the evidence is limited and mixed as to whether economic incentives can sustainably improve physical activity levels. The literature has examined the impact of personal economic incentives within micro-settings such as gym attendance (Charness and Gneezy, 2009; Royer et al., 2015). A recent literature review focused on randomised controlled trials (RCTs) concludes that there is no compelling evidence that economic incentives in these settings are effective upon the incentive's discontinuation, especially over the longer term (Finkelstein et al., 2019).[1] Existing RCTs focus on micro settings and follow up participants for short periods (i.e. one or two years typically).

This study presents quasi-experimental evidence on the long-term impact of economic incentive on physical activity at a population level. To date, such evidence is extremely scarce (Martin et al., 2012).[2] We focus specifically on active commuting in the form of walking or cycling. Because commuting is a habitual daily activity for many people, and because it is associated with significant broader health benefits (Dinu et al., 2019), it is an important target area for public policy interventions (Andersen, 2017).

[1] See Mantzari et al. (2015) for a similar conclusion; meanwhile, see Mitchell et al. (2020) for a more positive evaluation.

[2] Rare examples of the indirect effects of such "macro" policies or factors on physical activity have been identified by studies on the relationship between higher gasoline prices (induced by tax increases) and physical activity (see, for example, Courtemanche, 2011; Sen, 2012).

The London Congestion Charge (LCC) represents one of the world's most prominent transportation policies.[3] The LCC was implemented in 2003, imposing charges (initially £5 and then £10 per day) on most types of cars entering, exiting and operating within the Central London area. Although the policy's primary aim was to reduce congestion rather than directly promote physical activity, the associated increase in the cost of private car use may substantially incentivise active commuting in the area. For example, Pucher et al. (2012) rank the LCC as the policy with the most potential to encourage cycling in the city. Elsewhere, Maibach et al. (2009) describes the congestion charge as a policy option promoting increased physical activity on the basis of data indicating that cycling increased substantially in Central London following the LCC's implementation. Reviewing studies evaluating the different potential outcomes of the congestion charge (i.e. congestion, the environment, revenue and changes in travel behaviour), Givoni (2012) concludes that most findings suggest beneficial outcomes.[4] However, Givoni also expresses concerns about the extent to which these positive effects can be causally attributed to the LCC. A recent evaluation of the literature also recognises the need to produce more rigorous evidence of congestion pricing's impact on active commuting (Brown et al., 2015).

Despite prior investigations into the LCC's various direct and indirect outcomes, its potential effects on physical activity remain to be assessed via a formal impact evaluation. The most notable existing study, the findings of which are often cited in the related literature, is the series of reports by Transport for London, the local governmental body responsible for the city's transport services.[5] These reports provide detailed information on the changes observed for

[3] Some environmental and epidemiologic studies have addressed the potential health impacts of reduced air pollution in the Central London area (see, for example, Beevers et al., 2005; Tonne et al., 2008).
[4] See Tang (2021) for a more recent evaluation of the effect of the LCC on housing prices.

[5] The reports are available online at: http://www.tfl.gov.uk/roadusers/congestioncharging/6722.aspx (accessed September 2021).

different modes of travel, indicating that the amount of travel-related physical activity increased following the implementation of the LCC. For instance, cycling distances increased by about 30% after the charge's introduction (Transport for London, 2006). However, a major concern regarding such assessments is the difficulty of attributing the observed change exclusively to specific economic incentives deriving the scheme, given its introduction was accompanied by other significant changes in transportation policy, including improvements to bus networks and bicycle paths (Givoni, 2012).

To identify the effects of this economic incentive on active commuting, we analyse cases where the charge is discounted for individuals living inside the Central London area (i.e. inside the charging zone). These residents are eligible to have their charges reduced by 90%; meanwhile, those living outside the zone must pay the full amount. This significantly changes the incentive for those living just inside the charging zone compared to those living just outside it. Our estimation exploits this legislation by employing a boundary discontinuity design (Black, 1999; Dell, 2010).

Eligibility for the 90% discount is determined by postcode. We use a geographical information system (GIS) to geocode the charging zone's border and the residential locations of participants in the London Travel Demand Survey (LTDS) for the period 2005–2011. The data include full-digit postcode information, enabling precise calculation of the distance between residential locations and the charging zone's border, which we define as the treatment assignment variable. Using GIS, we also construct geographical segments of the study area, which we add as spatial fixed effects to our regression model, capturing time-invariant neighbourhood characteristics across the study area (Goldstein and Udry, 2008).

Our fixed-effect boundary discontinuity estimates for 2005-2011 show that the LCC's economic incentive did increase physical activity levels, as measured by the duration of time spent cycling and walking for travel purposes, but only modestly so, i.e. by about three minutes around the border of the charging zone. Exploiting an expansion of the charging zone to West London in 2007 reveals small and immediate effects of the economic incentive. The main effects are larger for lower-income households and car owners and are robust against multiple specifications and validation tests. Our overall findings suggest that the economic incentives exhibit immediate and persistent yet limited effects from a public health perspective on travel related physical activity. These do not fully support the long-standing aspirations for the LCC's economic incentive to increase physical activity levels, expressed in the epidemiological and public health literature.

The rest of the paper is organised as follows. Section 2 provides an overview of the LCC scheme. Section 3 describes our boundary discontinuity design. Section 4 explains the details of the data utilised. Section 5 reports the empirical findings, followed by extensions and robustness checks in Section 6. Finally, Section 7 concludes the paper.

2. The London Congestion Charge scheme

The idea of a congestion charge in London emerged in 1964 as a large-scale transportation policy with the main purpose of reducing congestion in the Central London area and using the revenue generated to improve the city's transport system. The scheme's economic rationale was built around the need to internalise the cost of congestion. As the cost of car travel within the zone increased, it was expected that congestion would retract to an optimal level of congestion, producing efficiency gains.

The LCC was implemented in February 2003, using the London Inner Ring Road as the charging zone's border. This approximately 20-kilometre-long route was included in the 1943 County of London Plan and established after World War II to comprise several major roads that surround the Central London area, including the City of London and the West End. Before the charge was implemented, about 25% of vehicles driving on the Inner Ring Road passed by the charging zone; hence, it was chosen as the border to enable such drivers to navigate the route without entering the zone (Leape, 2006).

The LCC scheme charges drivers of chargeable vehicles (i.e. private vehicles other than motorcycles, vehicles with nine or more seats and ultra-low-emission cars) when they enter, leave, travel through or park within the charging zone during the charging window, which is between 7:00 and 18:00 (changed from 18:30 in January 2007) Monday to Friday, excluding public holidays and the week of Christmas and New Year. Approximately 200 cameras operate across the charging zone, mostly around the border. Alongside "patrol" cars equipped with CCTV, these cameras photograph car number plates and send the images to a central system, which matches the images with driver information provided by the Driver and Vehicle Licensing Agency. Drivers are expected to take responsibility for paying the charge without being prompted to do so; that is, they are not notified that they have been captured within the charging zone unless they fail to pay, at which point a penalty notice is sent several days later. The initial rate was £5 per day if paid before 22:00 on the day of travel.[6] This was increased to £8 in July 2005 and then £10 in January 2010.

In February 2007, the charging zone was expanded to include western London, a largely residential area including the City of Westminster and parts of Kensington and Chelsea. Known as the "western expansion" (see Figure 1), this expansion was repealed in January 2011.

The scheme provides a resident discount, meaning that registered residents of areas within the charging zone (and some "buffer areas" just outside the zone) receive a 90% discount. In 2014, this discounted rate was £20 per month (if paid monthly); the full rate was £200 a month.

[6] In 2014, the standard rate was £10 per day if payment was made by 22:00 on the day of travel. The rate increased to £12 if paid the next day. If the driver failed to pay the charge, a penalty charge notice for £130 would be sent to the car owner. If the penalty charge was paid within 14 days, the charge was reduced to £65.

Eligibility for the discount is determined by the residential location's full postcode.[7] This creates a significant economic difference for those living outside the charging zone compared to those living inside the charging zone. Residents living inside the zone are not charged if their cars remain parked in a registered location during the charging window. However, upon driving their car, they risk being charged if they are captured by the cameras.

All revenues generated from the congestion fees are invested in improving transportation in the area. About 80% of the revenues are used to expand the local bus network and improve the services, including the number of services and a new payment system (Givoni, 2012). Also, there have been significant investments to promote cycling in the area, including the expansion of the cycling network, construction of cycling superhighways, establishment of new bicycle parking spaces and development of a bicycle-sharing scheme (Pucher et al., 2012; Martin et al., 2021).

According to earlier descriptive evidence, following the LCC's implementation, active travel increased, the number of cars entering Central London during the charging window decreased, and the number of bicycles entering the area increased (Transport for London, 2007). During the same period, the average distance cycled by residents increased by 30%, and the number of bus passengers (who tend to partake in more physical activity than door-to-door car drivers) increased substantially (Transport for London, 2006). Nonetheless, given that those related policies, implemented during the same period, might also have impacted active travel, the extent to which the economic incentive of the LCC prompted the observed changes in physical activity levels remains unclear.

[7] Transport for London operates a "zone checker" on their website, which informs residents whether they are eligible for the discount.

3. Methods

This study's primary goal is to estimate the causal effect of increasing the cost of chargeable sedentary travel modes (i.e. private car use) on travel-related physical activity levels. However, this estimation engenders at least two concerns. The first is a standard endogeneity problem related to residential location eligibility for the discount scheme; residential location is likely correlated with neighbourhood characteristics that independently determine travel modes, including the built environment (e.g. shops, roads, bus stops) and socioeconomic characteristics.

The second concern relates to isolating the effect of the congestion charge from effects produced by relevant complementary policies. As Section 2 discussed, the LCC's implementation was buttressed by other policies aimed at improving urban transportation, including improving the bus network and expanding cycling routes. As these complementary policies can also increase commuters' physical activity levels, an uncontrolled before-and-after comparison would fail to identify the LCC's causal effect.

To address these two concerns, we exploit the geographic discontinuity of eligibility for the discount. Focusing on individuals who live close to the charging zone's border, and thus share similar neighbourhood characteristics, mitigates concerns due to unobserved neighbourhood characteristics. Additionally, the benefits of improved urban transportation infrastructure are expected to be enjoyed almost equally by residents on both sides of the border. For example, if a person living on a border street has access to a better bus service, someone living on the opposite side of the street could easily utilise that same service. This suggests that the accompanying transportation policies are not likely to introduce bias to our analysis.

As mentioned, eligibility for the 90% discount is determined by postcode.[8] Our data contain full six-digit postcode information. Using a GIS, we locate each survey participant of LTDS within London (see Figure 1).

[Figure 1 about here]

In our analysis, the treatment group comprises individuals who live just outside the charging zone and pay the full congestion charge, and the control group comprises those who live just inside the zone and are eligible for the discount. Implementing a regression discontinuity design (RDD) estimation, we employ distance to the congestion charge area as the treatment assignment variable. To ensure we are comparing individuals who live close to each other, we follow the approach of Dell (2010) and implement a spatial RDD estimator that controls for border segment fixed-effect, by dividing the border into segments and assigning a segment identifier for each residential location. The same border segments are also used to cluster standard errors.[9]

To implement the boundary RDD, we follow the standard approach of the literature and run a local linear regression using the optimal mean squared error criterion with triangular kernel weights (Calonico et al., 2014)[10] as estimated by the following linear model:

$$y_{is} = \alpha + \tau LCC_{is} + \beta Dist_{is} * LCC_{is} + \pi Dist_{is}(1 - LCC_{is}) + \boldsymbol{z'}_i\boldsymbol{\gamma} + \varphi_s + \epsilon_{is}$$

[8] The Transport for London website offers a "charging zone checker" allowing residents to check whether they are eligible for the discount by entering their postcode: https://tfl.gov.uk/modes/driving/congestion-charge (accessed September 2021).

[9] We use the quantile-based method to divide the border into 50 segments of similar sample sizes. In two sensitivity analyses, we split the border into either 30 or 70 segments. This delivers similar results (see Appendix Table A1).

[10] Because the values of the forcing variable in our data are highly asymmetric (i.e. the minimum value of the forcing variable is 2 km inside the congestion charge zone and 29.5 km outside the zone) we allow for two different MSE-optimal bandwidth selectors for each side of the cut-off.

where y_{is} is the outcome variable for an individual i closer to the border segment s, α is the constant term and LCC_{is} is the treatment indicator, which equals 1 if the individual lives outside the congestion charge zone and 0 if they live inside the charge zone. On 9 February 2007, the charging zone was extended to the western side of Central London, making the LCC_{is} 0 if they were surveyed before 9 February 2007 and 1 if they were surveyed after that date.[11] We analyse the effects of the western expansion separately. The assignment variable $Dist_{is}$ is the distance to the border s from the the individual's residential location. The linear spline on the left side of the cut-off (i.e. inside the congestion charge zone) is represented by the interaction $Dist_{is} * LCC_{is}$, and $Dist_{is}\ (1 - LCC_{is})$ is the linear spline on the right side of the cut-off (i.e. outside the congestion charge zone). A sensitivity analysis also specifies a local quadratic spline. The spatial segment fixed effect proposed by Dell (2010) is represented by φ_s.

Finally, we control for a set of covariates in the vector $\boldsymbol{z}_{is}$, including calendar time (fixed effects for year, month, and day of the week), age (quadratic specification), gender, ethnicity (White, Asian, Other), employment status (employee, self-employed, student, non-employed, unknown status), possessing a driver's license, and household gross yearly income.

The literature indicates that the estimated treatment effect should be considered a weighted average treatment effect, where the weight is the probability of living close to the charging zone's border (see, for example, Lee and Lemieux, 2010). This raises concerns regarding the external validity of the estimated effects, which we acknowledge as a limitation of our approach.

[11] We run a series of placebo tests on false cut-off points by implementing an RDD estimation for every 2 km outside the congestion charge zone. We start from the second kilometre to have at least 2 km on the left of the false cut-off (as in the main analysis) and isolate the true discontinuity by removing units inside the congestion charge zone. Appendix Table A2 shows that no estimate for these false cut-off points is statistically significant at 5%.

4. Data

We use data from the LTDS for the period 2005–2011, beginning with the 2005/6 financial year. Unfortunately, data for the period between the congestion charge's implementation in 2003 and the middle of 2005 are not available, meaning our analysis addresses the congestion charge's long-term rather than immediate effects. The LTDS is an annual cross-sectional household survey for residents of London's boroughs and some parts of the area outside Greater London (restricted to those within the M25 motorway).

The sample households are representative in terms of both household characteristics and residential locations within the area. For each survey year, the total sample size is around 5,000 to 8,000, with a response rate of approximately 50–55%. Conducted via household interviews, the survey comprises three sets of questionnaires. The first is a household questionnaire addressing household characteristics (socioeconomic and demographic information),[12] vehicle ownership (i.e. how many and what kind of vehicles) and housing tenure (i.e. when the household began residing at the current residence). The second is an individual questionnaire completed by all household members aged five and above and covering individual-level demographic characteristics, including age and gender, employment or educational status, workplace/school details and travel-related characteristics, such as whether the individual possesses a driving license. A third questionnaire completed by all household members aged five or above provides information regarding trips made during the day before the household interview (i.e. a single-day travel diary) and records main travel mode, trip origin, trip

[12] If the household income band is missing, it is imputed using the following household characteristics: i) the number of full and part-time workers in the household; ii) household size and structure; iii) housing tenure; iv) whether the household has a home computer; v) number of vehicles available to the household; and vi) whether the household has another home.

destination, time of departure, time of arrival and trip purpose. Each trip is further divided into travel stages to also generate this information at the travel-stage level.[13]

Thus data include detailed geographic information, including full-digit postcode information for home, workplace and school addresses alongside detailed insights into resident travel behaviour. This enables us to use GIS to precisely geocode household locations and geographical characteristics of participant trips (e.g. distance). Although eligibility for the 90% reduction on the congestion charge derives from full postcode information, the data do not indicate whether eligible individuals actually registered to receive the discount. Accordingly, our effect estimates should be interpreted as intention-to-treat effects. The key outcome variables are the time spent on active travel (i.e. walking and cycling) and the distance travelled by car during the congestion charge window. The former derives from computing the time an individual spends on all travel stages involving either walking or cycling on the same day. Trips outside of the congestion charge window are recorded as zero.

Our initial sample includes 124,333 individuals, which we narrow down as follows. First, we remove individuals with missing information in their travel diaries (1,187 individuals). Second, we remove individuals for whom the treatment is unlikely to affect car use, such as individuals under 18 years old (28,426), those with long-term health problems or disabilities that limit their daily activity (10,090), and those who did not leave their place of residence during the day of the interview (16,066). Third, because the congestion charge only applies on weekdays and during working hours, we exclude travel data for weekends and public holidays (17,869 observations). Finally, we exclude 102 individuals who report values for trips during the congestion charge window positioning them above the 99.9 percentile for total time spent

[13] For an illustrative example, consider a trip to their workplace during which a person walks from their home to the nearest bus stop (stage 1) and then takes a bus to the city centre (stage 2) before walking to their workplace (stage 3). The total time spent walking during this trip is the sum of the durations of stages 1 and 3.

actively commuting (>326 minutes) or distance travelled by car (>285 km). Upon cleaning up the data, 50,593 observations remain.

5. Main results

Summary statistics

The analysis focuses on individuals living near the congestion charge zone's border. Table 1 presents summary statistics for two different subsamples: 1) inner London residents (individuals living within 2 km range of the charge zone border); and 2) the rest of the sample.

[Table 1 about here]

On average, the total time spent on active travel (walking or cycling) is half an hour per day per individual. Inner London residents spend more time on active travel than those in other areas (30 vs 22 minutes). Conversely, while inner London residents travel about 2.4 km in their cars per day, the rest of the sample travels about 8.1 km. This contrast could arise from inner London residents living closer to their workplace or school. No substantial differences are observed for distances covered by other means of transport (7 km) or for gender (52% are women). However, inner residents tend to be younger (40.6 vs 43.8 years old) and ethnically white (61% vs 55%). They also tend to report a lower gross household income and are more likely to be students (11.0% vs 6.0%). Finally, a smaller proportion of inner London residents possess a driver's license (64% vs 77%). No large differences are observed for calendar dates. Ultimately, differences between inner London residents and the rest of the sample implies that the travel environment in the inner London area is somewhat distinctive; as such, empirical findings from the inner London sample may not be generalisable to the broader London population.

Graphical analysis

We now graphically analyse our estimation sample after restricting it to the optimal bandwidth derived with reference to Calonico et al. (2014). Figure 2 plots the total duration of active travel and distance travelled by car during the day of travel against the distance between residential location and the charging zone border.

[Figure 2 about here]

In Figure 2, distance (horizontal axis) is 0 at the border; it is positive if an individual lives outside the border and negative if an individual lives inside the border. The plots demonstrate a small increase in the duration of active commuting and a small decrease in kilometres travelled by car for those living just outside the cut-off. The next subsection formally estimates these effects.

Regression analysis

Table 2 presents our benchmark regression analysis.

[Table 2 about here]

Panel A presents the effects on the total duration of active travel per individual per day. Column 1 indicates that the treatment effect is only about 3 extra minutes of active travel. The effect is statistically significant at 5% and is robust to different estimation methods, including incorporating individual covariates (Column 2) and relying on a quadratic spline (Column 3). Retaining only individuals with a car on the day of travel (Column 4) delivers larger effects (+7.8 minutes).[14] This implies that the economic incentive increases overall activity levels from

[14] No significant effect is found for the subset of individuals with no car available during the day.
These estimates are available upon request.

a statistical significance perspective, but only moderately so from a population health perspective.

Column 1 of Panel B demonstrates a reduction in the total distance travelled by car during the congestion charge window of only about 0.9 km. However, the effect is statistically significant at 10% for only some specifications, possibly owing to the inability to detect small reductions in car use. Finally, Panel C represents the statistically insignificant effect on the distance travelled using other means of transportation.

6. Extension and robustness

Income heterogeneity

According to our main results, the LCC has only a small overall impact on active commuting. A potential explanation for this finding is that the charge insufficiently disincentivises those who can already afford to live in the costly Central London area from driving. Accordingly, we estimate the heterogeneous effects for individuals above or below the median observed household income (£25,000). If the estimated effect is due to the economic incentive of the congestion charge area, and not due to something else, we should observe a larger effect for lower-income households. In Table 3, our estimates confirm this prediction (see Column 1 of Panel A): the effect on active commuting is larger and only statistically significant for individuals from lower-income households (+4.5 minutes). Results are robust to the inclusion of covariates (Column 2) or relying on a quadratic spline (Column 3). Similar differences between income groups are observed for the distance travelled by car during the day (Panel B).

[Table 3 about here]

Expansion of the charging zone and its repeal

Given the congestion charge was first implemented in 2003, but our data begins in the 2005/6 financial year, our main analysis should thus be viewed as assessing the long-term effects of the economic incentive. However, the aforementioned "western expansion", which occurred in February 2007 before being repealed in December 2010, can be exploited using the LTDS's time dimension to estimate the "border effect" for West London. We first implement a placebo test for when there was no congestion charge (before February 2007 and after December 2010) and then estimate the treatment effect during the period of the congestion charge. This analysis employs distance from the western border of the congestion charge area as the treatment assignment variable.[15]

In Table 4, we do not observe a statistically significant difference in travel behaviour for the period during which residents of the West London area were not eligible for a reduced congestion charge (Panel A). Instead, during the period of the expansion (Panel B), we estimate a higher level of active commuting among individuals living outside the Western congestion charge zone (about 3.9 minutes; Column 3) and a reduction in the distance travelled by car (1.9 km; Column 4), indicating an immediate but modest impact of the economic incentive on active travel.

[Table 4 about here]

Sorting around the charging zone

Depending on the availability of housing properties, individuals can choose where they live, which can violate a basic assumption of regression discontinuity design, namely, the lack of precise sorting around the cut-off (Black, 1999; Dell, 2010; Magruder, 2012). If individuals with

[15] We remove 737 individuals living in the central area due to there being no treatment difference along that border during the western expansion.

a preference for a sedentary lifestyle self-select to live inside the congestion charge zone to avoid such a charge, the effects of the economic incentive on active commuting would be overestimated, meaning the true effects would be even smaller than our main analysis' modest estimates.

To formally address this concern, we implement the density test proposed by Cattaneo et al. (2020, 2021) to explore potential manipulation around the cut-off. The test result does not reject the null hypothesis of a discontinuity in density at the cut-off, with the p-value being 0.340 (for a graphical representation, see Appendix Figure A1).

We test for compositional changes around the cut-off by running the same RDD estimator using each covariate as an alternative dependent variable. As Appendix Table A3 demonstrates, of the 45 estimates, only one (travel year = 2007) is statistically significant at 5%, which is below the 5% rejection rate of a false positive.

We further estimate the effect by restricting the sample to those who resided in the area before the congestion charge was implemented. In Table 5, Panel A reveals that the charge increases active commuting by 6.9 minutes and reduces the distance travelled by private car by 1.4 km; however, only the former is statistically significant. The magnitude of these impacts is slightly greater than the estimates using the full sample.

[Table 5 about here]

Travelling outside the congestion charge window

The congestion charge only applies from 7:00 to 18:00 on weekdays. Individuals might thus choose to commute before and after the charge window to avoid being charged. Accordingly, we estimate the effect of the congestion charge on the probability of travelling outside the charging hours, with Panel B of Table 5 revealing that the effect is not statistically significant for either the whole sample or for the subsample of individuals with a car available during the day, thereby rejecting the possibility of the economic incentive affecting when individuals choose to travel.

7. Concluding remarks

As reported by Transport for London, there have been increases in travel-related physical activity levels in the Central London area since the congestion charge's implementation. However, it has long been unclear whether this trend is indeed causally attributable to the congestion charge. While this study does observe statistically significant positive effects on active commuting overall, especially among car-owners and residents of lower-income households, the estimated magnitude suggests, at best, a very moderate impact on physical activity and health. Our findings do not support the high expectations expressed in the epidemiological and public health literature (Andersen, 2017), in terms of the effectiveness of economic incentives in increasing physical activity at the population level. This suggests that other related policies might have contributed substantially to the trend; these include the expansion of cycling routes and bicycle-rental schemes, which are partly funded by revenues generated by the congestion charge. This underscores the need for a more holistic, multi-component intervention approach, of which economic incentives represent one component, albeit a component that raises the revenue necessary to fund accompanying measures, thereby indirectly impacting active commuting.

The daily charge rate has been increased several times since the LLC's introduction (initially £5 per day; £8 from July 2005 to January 2010; £10 henceforth). While the estimates for travel before 2010 are consistent with the main results, our data do not provide sufficient power to detect significant effects after 2010 due to the small sample size,[16] precluding assessment of the impact of changes to the congestion charge.

Overall, our results have implications for policy-makers seeking to plan community-level economic incentives to stimulate a preferred behaviour. In a health context, as previous studies on gym attendance have demonstrated, personal economic incentive schemes are, at best, effective for one or two years (Charness and Gneezy, 2009; Royer et al., 2015). However, achieving sustained behavioural change in terms of physical activity – in this case, in the form of active commuting – may require either larger economic incentives or a set of adjacent interventions to accompany the economic incentive.

[16] The number of individuals living inside the congestion charge zone in the 2010-2011 data is only 193.

References

1. Andersen, L.B., 2017. Active commuting is beneficial for health. The BMJ. 357:j1740.
2. Beevers, S.D., Carslaw, D.C., 2005. The impact of congestion charging on vehicle emissions in London. Atmospheric Environment. 39(1):1-5.
3. Black, S.E., 1999. Do better schools matter? Parental valuation of elementary education. Quarterly Journal of Economics. 114(2):577-599.
4. Brown, V., Moodie, M., Carter, R., 2015. Congestion pricing and active transport–evidence from five opportunities for natural experiment. Journal of Transport & Health. 2(4):568-79.
5. Calonico, S., Cattaneo, M.D., Titiunik, R., 2014. Robust nonparametric confidence intervals for regression-discontinuity designs. Econometrica. 82(6):2295-2326.
6. Cattaneo, M.D., Jansson, M., Ma, X., 2020. Simple local polynomial density estimators. Journal of the American Statistical Association. 115(531):1449-145.
7. Cattaneo, M.D., Jansson, M., Ma, X., 2021. Local regression distribution estimators. Forthcoming in Journal of Econometrics.
8. Cawley, J., Ruhm, C.J., 2011. The economics of risky health behaviors. In: Handbook of Health Economics. 2:95-199.
9. Cawley, J., Thow, A.M., Wen, K., Frisvold, D., 2019. The economics of taxes on sugar-sweetened beverages: a review of the effects on prices, sales, cross-border shopping, and consumption. Annual Review of Nutrition. 21(39):317-38.
10. Charness, G., Gneezy, U., 2009. Incentives to exercise. Econometrica. 77(3): 909-931.
11. Courtemanche, C., 2011. A silver lining? The connection between gasoline prices and obesity. Economic Inquiry. 49(3):935-957.

12. Dell, M., 2010. The persistent effects of Peru's mining mita. Econometrica 78(6):1863-1903.

13. Dinu, M., Pagliai, G., Macchi, C., Sofi, F., 2019. Active commuting and multiple health outcomes: a systematic review and meta-analysis. Sports Medicine. 49(3):437-52.

14. Finkelstein, E.A., Bilger, M., Baid, D., 2019. Effectiveness and cost-effectiveness of incentives as a tool for prevention of non-communicable diseases: a systematic review. Social Science & Medicine. 232:340-50.

15. Giné, X., Karlan, D., Zinman, J., 2010. Put your money where your butt is: A commitment contract for smoking cessation. American Economic Journal: Applied Economics. 2(4):213-235.

16. Givoni, M., 2012. Re-assessing the results of the London congestion charging scheme. Urban Studies. 49(5):1089-1105.

17. Goldstein, M., Udry, C., 2008. The profits of power: land rights and agricultural investment in Ghana. Journal of Political Economy. 116(6):981-1022.

18. Gruber, J., Köszegi, B., 2001. Is addiction "rational"? Theory and evidence. Quarterly Journal of Economics. 116(4):1261-1303.

19. Leape, J., 2006. The London Congestion Charge. Journal of Economic Perspectives. 20(4):157-176.

20. Lee, D.S., Lemieux, T., 2010. Regression discontinuity designs in economics. Journal of Economic Literature. 48(2):281-355.

21. Magruder, J.R., 2012. High unemployment yet few small firms: the role of centralized bargaining in South Africa. American Economic Journal: Applied Economics. 4(3):138-166.

22. Maibach, E., Steg, L., Anable, J., 2009. Promoting physical activity and reducing climate change: opportunities to replace short car trips with active transportation. Preventive Medicine. 49(4):326-7.

23. Mantzari, E., Vogt, F., Shemilt, I., Wei, Y., Higgins, J.P., Marteau, T.M., 2015. Personal financial incentives for changing habitual health-related behaviors: a systematic review and meta-analysis. Preventive Medicine. 75:75-85.

24. Martin, A., Morciano, M., Suhrcke, M., 2021. Determinants of bicycle commuting and the effect of bicycle infrastructure investment in London: evidence from UK census microdata. Economics & Human Biology. 41:100945.

25. Martin, A., Suhrcke, M., Ogilvie, D., 2012. Financial incentives to promote active travel: an evidence review and economic framework. American Journal of Preventive Medicine. 43(6):e45-e57.

26. Mitchell, M.S., Orstad, S.L., Biswas, A., Oh, P.I., Jay, M., Pakosh, M.T., Faulkner, G., 2020. Financial incentives for physical activity in adults: Systematic review and meta-analysis. British Journal of Sports Medicine. 54(21):1259-68.

27. Pucher, J., de Lanversin, E., Suzuki, T., Whitelegg, J., 2012. Cycling in megacities: London, Paris, New York, and Tokyo. In: Pucher J & Buehler R (eds.) City Cycling. MIT Press, Cambridge MA.

28. Royer, H., Stehr, M.F., Sydnor, J.R., 2015. Incentives, commitments and habit formation in exercise: Evidence from a field experiment with workers at a Fortune-500 company. American Economic Journal: Applied Economics. 7(3):51-84.

29. Sen, B., 2012. Is there an association between gasoline prices and physical activity? Evidence from American time use data. Journal of Policy Analysis and Management. 31(2):338-66.

30. Tang, C.K., 2021. The Cost of traffic: Evidence from the London Congestion Charge. Journal of Urban Economics. 121:103302

31. Tonne, C., Beevers, S., Armstrong, B., Kelly, F., Wilkinson, P., 2008. Air pollution and mortality benefits of the London Congestion Charge: spatial and socioeconomic inequalities. Occupational and Environmental Medicine. 65(9):620-627.

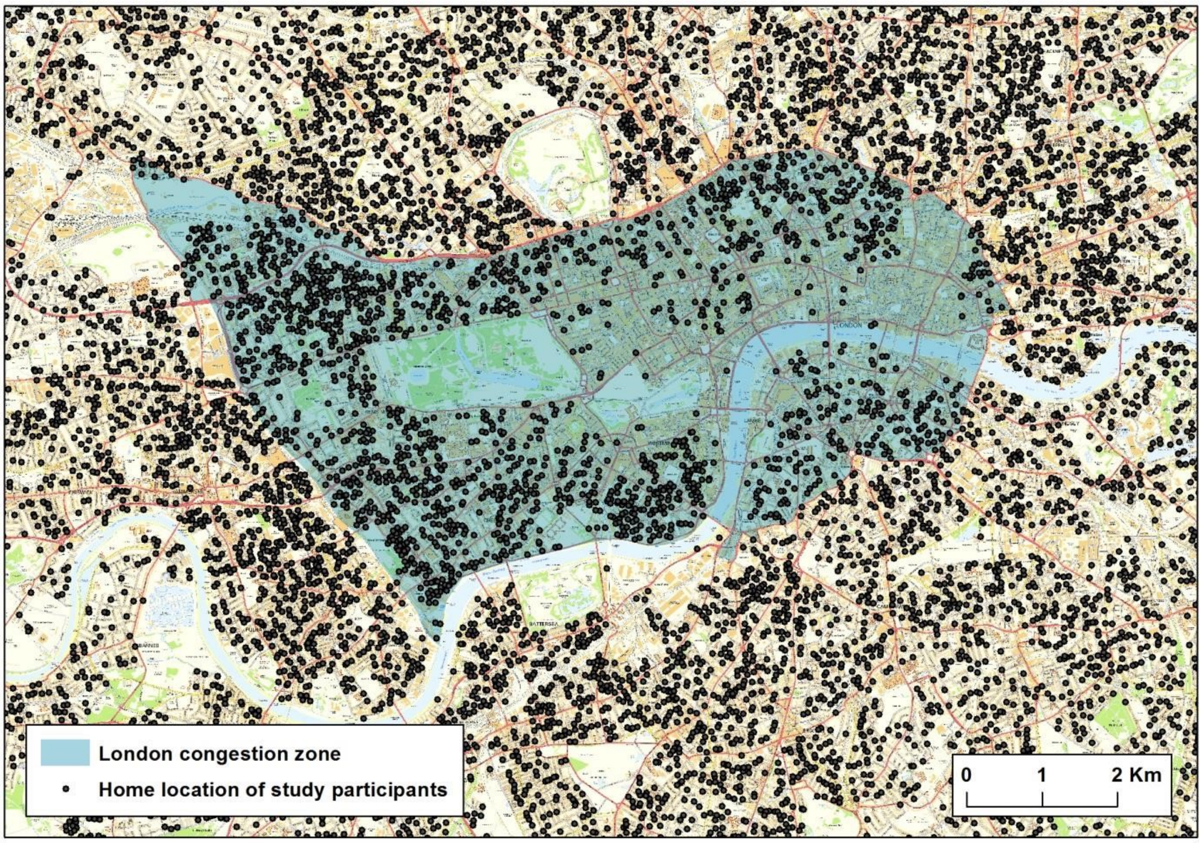
32. Transport for London, 2006. Central London congestion charging: Impacts monitoring. Fourth annual report. Mayor of London, London.

33. Transport for London, 2007. Central London congestion charging: Impacts monitoring. Fifth annual report. Mayor of London, London.

34. Volpp, K.G., Troxel, A.B., Pauly, M.V., Glick, H.A., Puig, A., Asch, D.A., Galvin, R., Zhu, J., Wan, F., DeGuzman, J., Corbett, E., Weiner, J., Audrain-McGovern, J., 2009. A randomized, controlled trial of financial incentives for smoking cessation. New England Journal of Medicine. 360:699-709.

35. Yaniv, G., Rosin, O., Tobol, Y., 2009. Junk-food, home cooking, physical activity and obesity: The effect of the fat tax and the thin subsidy. Journal of Public Economics. 93(5-6):823-830.

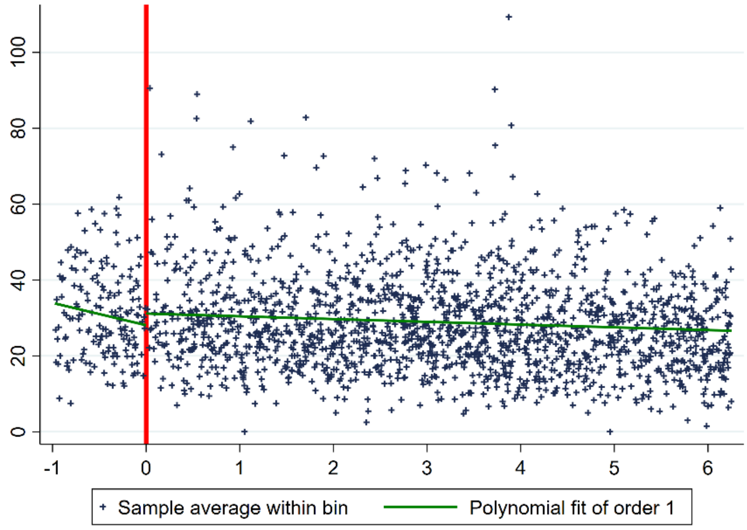
Figure 1: Distribution of study households (Central London area), LTDS, 2005–2011



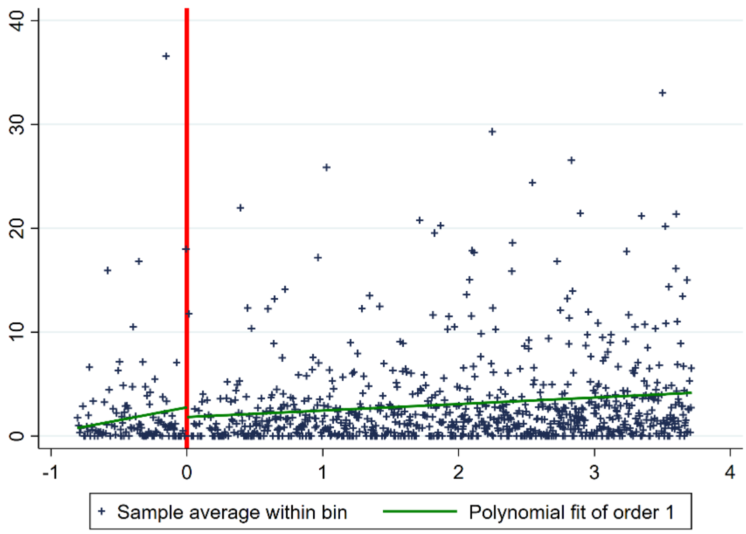
Note: The blue area represents the congestion charge area for the period between February 2007 and January 2011, when the charging zone incorporated the western expansion.

Figure 2: Graphical analysis of the boundary discontinuity at the border of the LLC zone (duration of active travel and kilometres travelled by car during the day)

A) Total duration of active travel in minutes



B) Total distance by car in kilometres



Note: These graphs show RDD plots for the following dependent variables: a) total duration of active travel (walking or cycling) in minutes and b) total distance by car during the day in km. The treatment assignment variable is the distance to the congestion charge zone from the residential location. The splines are obtained using a local linear polynomial regression with triangular weights and bandwidth following the two optimal MSE selectors for the two sides of the discontinuity in accordance with Calonico et al. (2014). We impose the variance quantile-spaced method using a spacings estimator to select the number of bins.

Table 1: Summary statistics (LTDS, 2005–2011)

	Inner London	Outside of inner London
Total active travel time during the congestion charge period (minutes)	30.49	22.43
(Standard deviation)	(32.87)	(31.12)
Total distance travelled by car during the congestion charge period (km)	2.41	8.08
(Standard deviation)	(10.99)	(19.33)
Total distance travelled by other transport means during the congestion charge period (km)	7.04	7.23
(Standard deviation)	(24.70)	(19.69)
Age (Mean)	40.65	43.85
Female	0.52	0.52
Ethnicity: Asian	0.07	0.04
Ethnicity: White	0.12	0.09
Ethnicity: Other	0.11	0.09
Income: below £5,000	0.11	0.09
Income: £5,000–9,999	0.10	0.09
Income: £10,000–14,999	0.13	0.14
Income: £15,000–19,999	0.11	0.16
Income: £20,000–24,999	0.12	0.15
Income: £25,000–34,999	0.06	0.08
Income: £35,000–49,999	0.09	0.07
Income: £50,000–74,999	0.09	0.14
Income: £75,000–99,999	0.61	0.55
Income: £100,000 and above	0.30	0.31
Employee	0.58	0.62
Self-employed	0.04	0.04
Unemployed or inactive	0.25	0.28
Unknown working status	0.03	0.00
Student	0.11	0.06
Driver's license holder	0.64	0.77
N	5,356	45,237

Note: Inner London includes individuals living within 2 kilometres of the charging zone border. Calendar time dummies are not reported.

Table 2: The effects of the LLC on (A) time spent actively travelling, (B) distance travelled by car and (C) distance travelled by other means of transport

	(A) Active travel time (minutes)			
	Local linear	**Local linear**	**Local quadratic**	**Local linear, car available**
	(1)	(2)	(3)	(4)
Beta	3.067**	3.816**	4.441	7.769**
Robust CI	[0.176 ; 8.404]	[0.862 ; 9.359]	[-2.754 ; 8.154]	[1.853 ; 18.124]
Robust p-value	0.041	0.018	0.332	0.016
Order Loc. Poly. [p]	1	1	2	1
Order Bias [q]	2	2	3	2
Covariates	No	Yes	Yes	Yes
Total N	50,593	50,593	50,593	36,494
Eff. N estimate [h]	14,950	12,368	23,336	6,532
Eff. N bias [b]	35,448	25,716	35,126	15,812

	(B) Distance travelled by car (km)			
	Local linear	**Local linear**	**Local quadratic**	**Local linear, car available**
	(1)	(2)	(3)	(4)
Beta	-0.934	-1.523*	-1.620	-3.317*
Robust CI	[-3.486 ; 1.127]	[-3.900 ; 0.333]	[-5.04 ; 1.718]	[-8.836 ; 0.329]
Robust p-value	0.316	0.099	0.335	0.069
Order Loc. Poly. [p]	1	1	2	1
Order Bias [q]	2	2	3	2
Covariates	No	Yes	Yes	Yes
Total N	50,593	50,593	50,593	36,494
Eff. N estimate [h]	9,180	9,353	16,966	5,092
Eff. N bias [b]	18,184	18,884	27,861	10,431

	(C) Distance travelled by other means of transport			
	Local linear	**Local linear**	**Local quadratic**	**Local linear, car available**
	(1)	(2)	(3)	(4)
Beta	-0.980	0.421	-0.578	-0.499
Robust CI	[-4.572 ; 1.110]	[-6.875 ; 4.998]	[-9.102 ; 6.133]	[-3.523 ; 2.64]
Robust p-value	0.232	0.757	0.702	0.779
Order Loc. Poly. [p]	1	1	2	1
Order Bias [q]	2	2	3	2
Covariates	No	Yes	Yes	Yes
Total N	50,593	50,593	50,593	36,494
Eff. N estimate [h]	13,853	13,110	15,949	11,335
Eff. N bias [b]	30,109	24,785	24,769	28,244

Notes: The dependent variables are (A) time (in minutes) of active travel undertaken during the day, (B) the distance travelled by car during the day (km) and (C) the distance travelled by other means of transport during the day (km). RDD estimates use distance from residential location to the congestion charge zone as the treatment assignment variable. The table presents results from a local regression with triangular weights. Two different MSE-optimal bandwidth selectors for the two sides of the discontinuity are used, as in Calonico et al. (2014). The models control for and cluster into 50 border segments (Dell, 2010). Different models: (1) local linear regression without covariates, (2) local linear regression with covariates, (3) local quadratic regression with covariates, (4) local linear regression with covariates on the subsample of individuals with a car available during the day. The table shows the total number of observations (N) and the effective number of observations for the estimates (h) and the bias (b). Robust bias-corrected *p*-value and confidence intervals are reported. * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Table 3: Heterogeneous effects by household income of the LLC on (A) active travel time and (B) distance travelled by car

	(A) Active travel time (minutes)					
	Lower-income households			Higher-income households		
	Local linear	Local linear	Local quadratic	Local linear	Local linear	Local quadratic
	(1)	(2)	(3)	(4)	(5)	(6)
Beta	4.564***	5.708***	8.306***	1.187	1.557	-1.769
Robust CI	[3.009 ; 12.956]	[3.612 ; 14.093]	[5.292 ; 17.012]	[-8.076 ; 7.191]	[-7.337 ; 6.659]	[-14.778 ; 2.829]
Robust p-value	0.002	0.001	0.000	0.909	0.924	0.183
Order Loc. Poly. [p]	1	1	2	1	1	2
Order Bias [q]	2	2	3	2	2	3
Covariates	No	Yes	Yes	No	Yes	Yes
Total N	21,020	21,020	21,020	29,573	29,573	29,573
Eff. N estimate [h]	6,368	6,322	11,135	6,668	7,022	15,150
Eff. N bias [b]	13,598	14,133	15,511	16,561	16,832	23,453

	(B) Distance travelled by car (km)					
	Lower-income households			Higher-income households		
	Local linear	Local linear	Local quadratic	Local linear	Local linear	Local quadratic
	(1)	(2)	(3)	(4)	(5)	(6)
Beta	-1.548	-2.123*	-4.261**	-0.993	-1.618	-0.851
Robust CI	[-5.506 ; 0.850]	[-5.940 ; 0.115]	[-10.626 ; -0.207]	[-4.356 ; 2.030]	[-4.883 ; 1.343]	[-2.839 ; 3.665]
Robust p-value	0.151	0.059	0.042	0.475	0.265	0.803
Order Loc. Poly. [p]	1	1	2	1	1	2
Order Bias [q]	2	2	3	2	2	3
Covariates	No	Yes	Yes	No	Yes	Yes
Total N	21,020	21,020	21,020	29,573	29,573	29,573
Eff. N estimate [h]	5,089	4,951	11,008	4,779	4,807	8,117
Eff. N bias [b]	10,142	10,174	15,443	9,144	9,255	13,903

Notes: The dependent variables are (A) time (in minutes) of active travel undertaken during the day and (B) the distance travelled by car during the day (km). Subsample: lower-income households with a gross yearly income below £25,000 and higher income households with a gross yearly income above £25,000. RDD estimates use distance from residential location to the congestion charge zone as the treatment assignment variable. The table presents results from a local regression with triangular weights. Two different MSE-optimal bandwidth selectors for the two sides of the discontinuity are used, as in Calonico et al. (2014). The models control for and cluster into 50 border segments (Dell, 2010). Different models: (1, 4) local linear regression not controlling for individual covariates, (2, 5) local linear regression controlling for individual covariates, (3, 6) local quadratic regression controlling for individual covariates. The table shows the total number of observations (N) and the effective number of observations for the estimates (h) and the bias (b). Robust bias-corrected *p*-value and confidence intervals are reported. * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Table 4: The effects of the congestion charge on participants in the western border zone (A) in placebo periods and (B) during the western expansion

	(A)		(B)	
	Placebo: before or after the western expansion		**During the western expansion**	
	Active travel time (minutes)	**Distance travelled by car (km)**	**Active travel time (minutes)**	**Distance travelled by car (km)**
	(1)	(2)	(3)	(4)
Beta	-3.746	-0.515	3.949**	-1.921*
Robust CI	[-20.412 ; 6.253]	[-3.329 ; 1.542]	[0.034 ; 11.02]	[-5.073 ; .397]
Robust p-value	0.298	0.472	0.049	0.094
Order Loc. Poly. [p]	1	1	1	1
Order Bias [q]	2	2	2	2
Covariates	Yes	Yes	Yes	Yes
Total N	21,674	21,674	28,182	28,182
Eff. N estimate [h]	3,454	4,398	4,398	2,996
Eff. N bias [b]	8,920	11,702	11,509	7,226

Notes: The analyses concern (A) trips before or after the western expansion period and (B) trips during the western expansion period. The dependent variables are: (1, 3) time (in minutes) of active travel undertaken during the day; and (2, 4) the distance travelled by car during the day (km). RDD estimates use distance from residential location to the congestion charge zone as the treatment assignment variable. The table presents results from a local linear polynomial regression with triangular weights.Two different MSE-optimal bandwidth selectors for the two sides of the discontinuity are used, as in Calonico et al. (2014). The modelscontrol for and cluster into 50 border segments (Dell, 2010). We control for individual covariates as described in Section 3. The table shows the total number of observations (N) and the effective number of observations for the estimates (h) and the bias (b). Robust bias-corrected *p*-value and confidence intervals are reported. * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

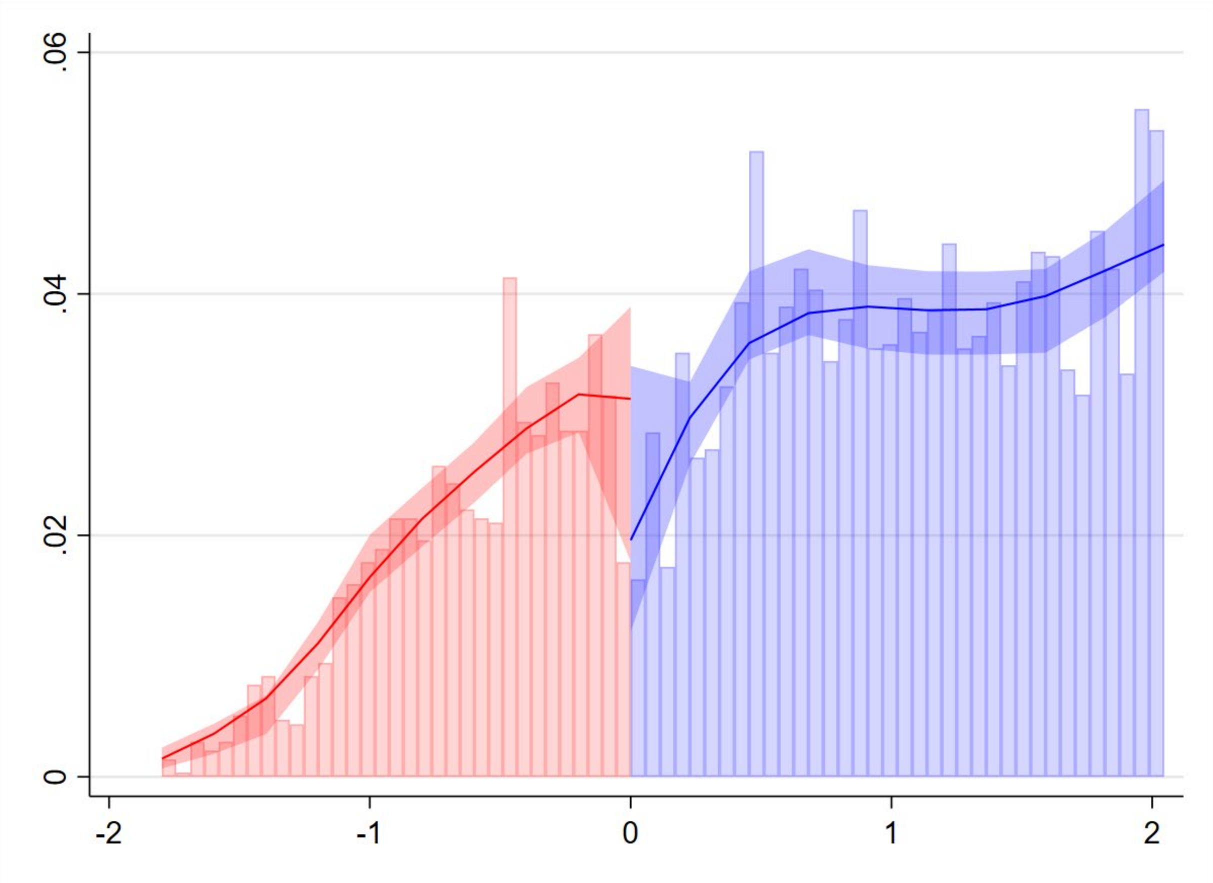
Table 5: The effect of the LCC on (A) individuals already residing in border zones and (B) individuals travelling outside the charging window

	(A)		(B)	
	Active travel time (minutes)	**Distance travelled by car (km)**	**Travelling outside the charging window (full sample)**	**Travelling outside the charging window (car users)**
	(1)	(2)	(3)	(4)
Beta	6.869***	-1.444	-0.015	-0.057
Robust CI	[4.927 ; 16.058]	[-4.681 ; 1.272]	[-0.086 ; 0.074]	[-0.195 ; 0.109]
Robust p-value	0.000	0.262	0.882	0.579
Order Loc. Poly. [p]	1	1	1	1
Order Bias [q]	2	2	2	2
Covariates	Yes	Yes	Yes	Yes
Subsample	No movers	No movers	All	Car available
Total N	28,781	28,781	50,593	36,494
Eff. N estimate [h]	6,431	4,229	10,476	7,898
Eff. N bias [b]	14,072	9,085	20,132	18,908

Notes: The dependent variables are: (1) time (in minutes) of active travel undertaken during the day, (2) the distance travelled by car during the day (km) and (3, 4) the probability of travelling outside the congestion charge hours. RDD estimates use distance from residential location to the congestion charge zone as the treatment assignment variable. The table presents results from a local linear polynomial regression with triangular weights.Two different MSE-optimal bandwidth selectors for the two sides of the discontinuity are used, as in Calonico et al. (2014). The models control for and cluster into 50 border segments (Dell, 2010). We control for individual covariates as described in Section 3. Subsamples: (1, 2) participants who lived in their place of residence before the LLC's implementation (no movers); (3) all participants; and (4) participants with a car available during the day. The table shows the total number of observations (N) and the effective number of observations for the estimates (h) and the bias (b). Robust bias-corrected *p*-value and confidence intervals are reported. * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Appendix (not for publication)

Appendix Figure A1: Density test over distance from border



Notes: Manipulation test uses the local polynomial density estimators proposed by Cattaneo et al. (2020, 2021). A local quadratic approximation with kernel triangular weights is used to construct the density estimators, and a cubic approximation is used for the bias-corrected density estimator. The density estimation method is unrestricted (two-sample). Robust bias-corrected statistic with jackknife standard errors and uniform confidence interval at 95% level (2000 simulations). Stata command rddensity is used.

Appendix Table A1: Changing the number of border segments

	(A)		(B)	
	30 segments		70 segments	
	Active travel time (minutes)	Distance travelled by car (km)	Active travel time (minutes)	Distance travelled by car (km)
	(1)	(2)	(3)	(4)
Beta	4.012**	-1.360	4.352**	-1.598*
Robust CI	[0.671 ; 10.236]	[-3.776 ; 0.678]	[1.098 ; 9.898]	[-3.945 ; 0.177]
Robust p-value	0.025	0.173	0.014	0.073
Order Loc. Poly. [p]	1	1	1	1
Order Bias [q]	2	2	2	2
Covariates	Yes	Yes	Yes	Yes
Subsample	All	Car available	All	Car available
Total N	50,593	50,593	50,593	50,593
Eff. N estimate [h]	13,521	10,129	12,080	9,277
Eff. N bias [b]	28,129	20,022	25,607	18,876

Notes: The dependent variables are (1, 3) time (in minutes) of active travel undertaken during the day and (2, 4) the distance travelled by car during the day (km). RDD estimates use distance from residential location to the congestion charge zone as the treatment assignment variable. The table presents results from a local linear polynomial regression with triangular weights. Two different MSE-optimal bandwidth selectors for the two sides of the discontinuity are used, as in Calonico et al. (2014). The models control for and cluster into 30 (A) and 70 (B) border segments (Dell, 2010). Note that the main analysis uses 50 border segments. We control for individual covariates as described in Section 3. The sample includes all participants with a car available during the day. The table shows the total number of observations (N) and the effective number of observations for the estimates (h) and the bias (b). Robust bias-corrected *p*-value and confidence intervals are reported. * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Appendix Table A2: Placebo tests (effect at false cut-offs)

	Beta	Robust CI	Robust p-value	Order Loc. Poly. [p]	Order Bias [q]	Total N	Eff. N estimate [h]	Eff. N bias [b]
Cut-off (2)								
Active travel time (minutes) (A, 1)	1.157	[-2.510 ; 4.841]	0.534	1	2	48,981	16,090	34,212
Active travel time (minutes) (A, 2)	1.041	[-3.892 ; 5.851]	0.694	2	3	48,981	18,250	28,588
Distance travelled by car (km) (B, 1)	-0.308	[-1.644 ; 1.019]	0.645	1	2	48,981	14,958	32,063
Distance travelled by car (km) (B, 2)	0.041	[-1.467 ; 1.971]	0.774	2	3	48,981	18,991	30,664
Cut-off (4)								
Active travel time (minutes) (A, 1)	-1.059	[-3.164 ; 1.139]	0.356	1	2	48,981	18,293	31,737
Active travel time (minutes) (A, 2)	-1.391	[-5.094 ; 1.504]	0.286	2	3	48,981	32,462	38,590
Distance travelled by car (km) (B, 1)	0.674	[-0.419 ; 2.152]	0.186	1	2	48,981	13,580	29,862
Distance travelled by car (km) (B, 2)	0.573	[-0.940 ; 2.223]	0.426	2	3	48,981	17,484	28,632
Cut-off (6)								
Active travel (minutes) (A, 1)	1.878	[-0.404 ; 4.405]	0.103	1	2	48,981	15,195	30,088
Active travel (minutes) (A, 2)	2.428	[-0.791 ; 6.033]	0.132	2	3	48,981	23,013	34,363
Distance travelled by car (km) (B, 1)	-0.444	[-1.939 ; 0.978]	0.518	1	2	48,981	11,428	25,914
Distance travelled by car (km) (B, 2)	-0.326	[-2.256 ; 1.792]	0.822	2	3	48,981	17,950	29,268
Cut-off (8)								
Active travel time (minutes) (A, 1)	0.632	[-1.351 ; 3.122]	0.438	1	2	48,981	18,333	30,900
Active travel time (minutes) (A, 2)	1.150	[-2.023 ; 4.573]	0.449	2	3	48,981	22,910	31,198
Distance travelled by car (km) (B, 1)	0.278	[-1.041 ; 1.722]	0.629	1	2	48,981	18,300	29,072
Distance travelled by car (km) (B, 2)	0.479	[-1.216 ; 2.181]	0.578	2	3	48,981	26,571	34,458
Cut-off (10)								
Active travel time (minutes) (A, 1)	0.042	[-2.610 ; 2.448]	0.950	1	2	48,981	18,113	31,318
Active travel time (minutes) (A, 2)	-0.091	[-3.361 ; 3.085]	0.933	2	3	48,981	25,740	31,792
Distance travelled by car (km) (B, 1)	-0.640	[-2.146 ; 0.598]	0.269	1	2	48,981	14,242	23,643
Distance travelled by car (km) (B, 2)	-0.788	[-2.487 ; 0.737]	0.288	2	3	48,981	22,166	29,565
Cut-off (12)								
Active travel time (minutes) (A, 1)	1.141	[-0.803 ; 3.221]	0.239	1	2	48,981	17,723	30,391
Active travel time (minutes) (A, 2)	1.843	[-0.445 ; 4.877]	0.103	2	3	48,981	24,960	32,664
Distance travelled by car (km) (B, 1)	-0.980*	[-2.321 ; 0.151]	0.085	1	2	48,981	15,238	24,470
Distance travelled by car (km) (B, 2)	-1.011	[-2.562 ; 0.471]	0.177	2	3	48,981	20,177	28,156
Cut-off (14)								
Active travel time (minutes) (A, 1)	0.627	[-1.411 ; 2.450]	0.598	1	2	48,981	9,647	20,795
Active travel time (minutes) (A, 2)	-0.011	[-2.219 ; 2.009]	0.922	2	3	48,981	20,022	32,078
Distance travelled by car (km) (B, 1)	0.431	[-0.795 ; 1.815]	0.444	1	2	48,981	15,408	27,163
Distance travelled by car (km) (B, 2)	0.644	[-1.132 ; 2.477]	0.465	2	3	48,981	20,505	28,054
Cut-off (16)								
Active travel time (minutes) (A, 1)	1.664	[-0.977 ; 4.667]	0.200	1	2	48,981	15,521	29,671
Active travel time (minutes) (A, 2)	2.633	[-0.924 ; 6.720]	0.137	2	3	48,981	21,323	29,283
Distance travelled by car (km) (B, 1)	-0.698	[-2.700 ; 1.262]	0.477	1	2	48,981	14,592	30,711
Distance travelled by car (km) (B, 2)	-0.932	[-3.563 ; 1.261]	0.350	2	3	48,981	21,818	30,690

Notes: The dependent variables are A) time (in minutes) of active travel undertaken during the day and B) the distance travelled by car during the day (km). RDD estimates use distance from residential location to the congestion charge zone as the treatment assignment variable. Placebo cut-offs every two kilometers outside the congestion charge zone. To isolate the treatment effect, we retain only units to the right of the discontinuity. The table presents results from a local linear (1) or quadratic (2) polynomial regression with triangular weights. Two different MSE-optimal bandwidth selectors for the two sides of the discontinuity are used, as in Calonico et al. (2014). The models control for and cluster into 50 border segments (Dell, 2010). We control for individual covariates as described in Section 3. The table shows the total number of observations (N) and the effective number of observations for the estimates (h) and the bias (b). Robust bias-corrected *p*-value and confidence intervals are reported. * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Appendix Table A3: Discontinuity of covariates at the cut-off

	Beta	Robust CI	Robust p-value	Order Loc. Poly. [p]	Order Bias [q]	Covariates	Subsample	Total N	Eff. N estimate [h]	Eff. N bias [b]
Age	0.891	[-1.20 ; 5.44]	0.211	1	2	No	All	50,593	15,427	27,043
Female	0.017	[-0.07 ; 0.09]	0.808	1	2	No	All	50,593	12,294	22,309
Income: <£5,000	-0.028	[-0.08 ; 0.01]	0.109	1	2	No	All	50,593	26,262	38,647
Income: £5,000–9,999	-0.020	[-0.10 ; 0.04]	0.405	1	2	No	All	50,593	9,983	19,117
Income: £10,000–14,999	-0.055	[-0.11 ; 0.02]	0.178	1	2	No	All	50,593	13,546	23,503
Income: £15,000–19,999	0.029	[-0.03 ; 0.10]	0.330	1	2	No	All	50,593	13,135	22,847
Income: £20,000–24,999	0.013	[-0.03 ; 0.07]	0.375	1	2	No	All	50,593	15,741	27,092
Income: £25,000–34,999	0.035	[-0.01 ; 0.11]	0.133	1	2	No	All	50,593	15,830	28,625
Income: £35,000–49,999	-0.001	[-0.07 ; 0.04]	0.634	1	2	No	All	50,593	14,400	26,370
Income: £50,000–74,999	-0.002	[-0.09 ; 0.07]	0.769	1	2	No	All	50,593	13,449	25,473
Income: £75,000–99,999	0.028	[-0.02 ; 0.07]	0.331	1	2	No	All	50,593	15,356	28,189
Income: £100,000 +	0.016	[-0.04 ; 0.08]	0.514	1	2	No	All	50,593	14,942	24,739
Ethnicity: Asian	0.038	[-0.03 ; 0.10]	0.308	1	2	No	All	50,593	6,347	13,549
Ethnicity: White	-0.032	[-0.16 ; 0.06]	0.421	1	2	No	All	50,593	8,362	14,610
Ethnicity: Other	0.005	[-0.08 ; 0.11]	0.723	1	2	No	All	50,593	11,248	21,071
Employee	0.081	[-0.043 ; 0.205]	0.201	1	2	No	All	50,593	20,004	33,906
Self-employed	-0.016	[-0.051 ; 0.03]	0.614	1	2	No	All	50,593	13,079	21,798
Non-employed	-0.028	[-0.098 ; 0.088]	0.920	1	2	No	All	50,593	17,843	33,907
Student	-0.005	[-0.076 ; 0.055]	0.758	1	2	No	All	50,593	19,689	28,886
Driver's license holder	-0.037	[-0.121 ; 0.013]	0.114	1	2	No	All	50,593	10,441	21,021
Monday	0.01	[-0.059 ; 0.093]	0.653	1	2	No	All	50,593	17,612	33,749
Tuesday	-0.02	[-0.094 ; 0.094]	0.997	1	2	No	All	50,593	18,615	37,562
Wednesday	-0.043	[-0.126 ; 0.059]	0.477	1	2	No	All	50,593	20,598	35,073
Thursday	0.021	[-0.027 ; 0.164]	0.161	1	2	No	All	50,593	13,821	25,507
Friday	-0.014	[-0.171 ; 0.061]	0.351	1	2	No	All	50,593	14,694	27,875
2005	-0.013	[-0.037 ; 0.017]	0.466	1	2	No	All	50,593	11,451	20,751
2006	-0.007	[-0.124 ; 0.079]	0.662	1	2	No	All	50,593	10,042	18,368
2007	0.056***	[0.032 ; 0.185]	0.006	1	2	No	All	50,593	12,221	21,970
2008	-0.015	[-0.153 ; 0.061]	0.400	1	2	No	All	50,593	20,764	36,066
2009	0.011	[-0.054 ; 0.124]	0.443	1	2	No	All	50,593	12,492	24,594
2010	0.025	[-0.07 ; 0.13]	0.578	1	2	No	All	50,593	11,016	18,356
2011	-0.034	[-0.18 ; 0.06]	0.318	1	2	No	All	50,593	8,286	16,351

2012	-0.004	[-0.06 ; 0.04]	0.783	1	2	No	All	50,593	20,039	34,152
January	-0.064	[-0.15 ; 0.07]	0.451	1	2	No	All	50,593	13,029	22,956
February	-0.026	[-0.11 ; 0.07]	0.683	1	2	No	All	50,593	17,330	31,611
March	-0.001	[-0.12 ; 0.07]	0.632	1	2	No	All	50,593	18,156	30,453
April	-0.054	[-0.09 ; 0.04]	0.488	1	2	No	All	50,593	9,135	19,544
May	0.03	[-0.07 ; 0.10]	0.754	1	2	No	All	50,593	11,854	20,864
June	0.021	[-0.07 ; 0.08]	0.868	1	2	No	All	50,593	21,070	35,901
July	0.03	[-0.04 ; 0.12]	0.301	1	2	No	All	50,593	14,938	26,865
August	-0.013	[-0.08 ; 0.06]	0.790	1	2	No	All	50,593	11,236	18,995
September	-0.015	[-0.05 ; 0.06]	0.905	1	2	No	All	50,593	7,524	16,864
October	0.070*	[-0.00 ; 0.14]	0.061	1	2	No	All	50,593	15,191	32,907
November	-0.043	[-0.16 ; 0.07]	0.463	1	2	No	All	50,593	18,885	29,265
December	0.000	[-0.04 ; 0.05]	0.902	1	2	No	All	50,593	12,504	21,941

Notes: The dependent variables are the covariates listed in Section 3. RDD estimates use distance from residential location to the congestion charge zone as the treatment assignment variable. The table presents results from a local linear polynomial regression with triangular weights. Two different MSE-optimal bandwidth selectors for the two sides of the discontinuity are used, as in Calonico et al. (2014). The models control for and cluster into 50 border segments (Dell, 2010). The table shows the total number of observations (N) and the effective number of observations for the estimates (h) and the bias (b). Robust bias-corrected *p*-value and confidence intervals are reported. * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.