To Drive or Not to Drive: A Field Experiment in Road Pricing

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Abstract

We use a large field experiment to study how drivers respond to road use charges. The experiment collected six-second location data from GPS transponders installed in 1400 vehicles over a nine month period and implemented different prices via a system of credit accounts. We find an average price elasticity of -0.13 to uniform per kilometer charges, which is consistent with the literature on short-term demand response to fuel price increases. Uniform road charges lead primarily to reductions in high-speed driving and off-peak road use. Charges targeted at peak times or central areas are more successful in reducing driving under road conditions typically associated with congestion. We find no evidence of higher prices changing commuting patterns; drivers adjust primarily by taking fewer trips each week to malls and shops. We also document that because low-income drivers contribute least to congestion externalities and respond most to road use charges, they would be better off if existing sources of road revenues were replaced with fees that better reflect each driver's contribution to road use externalities.

Keywords: Congestion pricing, urban transportation, distributional concerns, public transport
JEL Codes: H22, H23, Q04, Q05, Q31, R02, R04

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1 Introduction

In 2016 the average commuter in Los Angeles spent over 100 hours in gridlock. In congested cities, peak hour travel in the latest model automobile can be slower than commutes 100 years ago with a horse and cart. Traffic jams cost U.S. drivers an average of $1,400 a year in wasted time and fuel costs.[1] Over 50% of the world's population lives in cities; this percentage is expected to rise to 70% over the next few decades.[2] As cities expand worldwide, the costs of traffic congestion will only continue to increase.

Supply-based solutions are notoriously ineffective at reducing congestion (Duranton and Turner (2011)). On the other hand, demand-based measures like road use charges, have been promoted by economists and transportation planners for years (Vickrey (1963), Vickrey (1969)). When roads are congested, each additional driver lowers the speed for other drivers. Congestion is a classic externality: drivers don't take into account how much their presence may increase drive times for others. Prices that reflect the cost that individual drivers impose on the system could encourage some drivers to shift to less congested times or other modes or routes. If designed well, road use charges could make the transportation system more efficient, cutting travel times and minimizing the disruption caused by unexpected delays.

New advances in electronic tolling and real-time kinematic GPS receivers are dramatically reducing the cost of implementing targeted road use charges. Systems that dynamically price all roads at all times are soon going to be technologically cost-effective (see Cramton et al. (2018) for an innovative proposal modeled on wholesale electricity markets). In the meantime, cities have started to take advantage of these technologies to implement road use fees that more closely mirror the congestion externality. There are, for example, road-access tolls that vary with time of day (San Francisco's Bay Bridge) or road conditions (express lanes near San Diego, Los Angeles, and Washington DC). Several cities have also imposed charges for accessing or using an entire geographical area (Singapore, London, Stockholm, Milan) and others are weighing similar proposals (New York, Vancouver).

But widespread adoption of congestion-based charges is hindered by a public concern that they would price the poor off the road for the convenience of the wealthy (Stupp (2018), Linn et al. (2016)). There is also the fear that the inframarginal tax burden may fall disproportionately on households in areas with inadequate provision of public transport alternatives (Goodman (2017)).

This paper provides insights into the distributional costs of congestion charges using a large field experiment that collects high-frequency data on driving behavior. We first use baseline driving patterns to document who wins and loses in how we currently pay for roads. We then identify the margins of adjustment, in the short run, of pricing differently. Specifically, we look at who responds to different prices, and on what types of trips.

The road pricing experiment installed GPS devices for eight to ten months in the primary vehicles of a random sample of 1400 households from a large metropolitan area of 4.7 million people in 2015-2016. The transponders collected six-second location data whenever vehicles were in motion. After a baseline period, treatment groups faced different sets of road use charges via a system of virtual accounts.

Because we only treat a small sample of the population, we do not expect our experiment to visibly change road conditions. We can, however, document the extent to which different charges reduce driving

[1]Estimates and comparison from INRIX 2017 Global Scorecard.
[2]UN (2016)

on typically-congested roads and at typically-congested times. In addition, one innovation in this paper is to propose a new method for evaluating future road pricing experiments. We create profiles for every household of how much time they spend at different speeds when driving. We then show how that distribution changes, in the aggregate, when households face different prices. Under new prices, do drivers spend less time at the high speeds that are representative of uncongested roads? Or do they spend less time at speeds that are likely to represent standstill or stop-and-go traffic?

Our results describe prices that changed for two to three months. We are not in a position to comment on who might start driving if roads become less congested, or how drivers might re-optimize their travel patterns given new expectations of travel times. We also cannot comment on what might happen to long-run migration patterns if improving road conditions changes the relative advantage of living close or far from the city center. That said, the short-run is important: any reshuffling of fees that can't deliver traffic relief in the first months of implementation is unlikely to have political support.

This paper makes several contributions. First, it provides insights into how targeted road use charges may need to be in order to actually reduce congestion. Parry and Small (2005) and Langer, Maheshri and Winston 2017 advocate for a tax on kilometers traveled as an alternative to fuel taxes. They show that the time costs of road congestion are by far the biggest externality in road transport, much larger than the costs of pollution. Hybrid and electric vehicles use much less petrol yet contribute equally to time delays. The authors argue in favor of a vehicle-mile traveled (VMT) charge, in order to better target the primary externality. We support policies that more directly target congestion, and we show in this paper that a uniform VMT charge is unlikely to be targeted enough. We find that under a constant 10 cents per kilometer fee, which doubles the average fuel cost of each kilometer driven, the kilometers that households reduce are primarily those driven under uncongested road conditions.

In contrast, we find that VMT charges that vary by time of day and VMT charges coupled with a cordon charge reduce the amount of time that households spend driving at low speeds. They also reduce use of highly-congested local arterial roads at peak times. We consider a treatment where weekday peak periods are charged at 15 cents per kilometer while all other times are charged at 8 cents per kilometer. Under this time-of-day pricing, we observe households reducing peak use, especially in the afternoons. We also consider an 8 cents distance-based charge that is coupled with an $8 cordon charge for every day a driver enters the typically highly-congested downtown area. Under the cordon charge, we observe reductions in cordon entry, driving within the cordon, and driving on congested roads leading into the cordon. That said, these reductions occur primarily on weekends, which were not targeted, and are less congested.

A major contribution of this paper is to be able to document, for the first time, who responds to road prices and on what margins. Historically, researchers have evaluated congestion charges using aggregate traffic flows (Foreman (2016), Leape (2006), Gibson and Carnovale (2015)) self-reported travel diaries (Karlström and Franklin (2009)), or telephone surveys (Small et al. (2005)). In the first case, the researchers can observe all of the vehicles with certainty, but don't know who is on the road or where they are going. In the latter cases, researchers may have detailed data on demographics and reported destinations, but limited information on the details of road use. By being able to simultaneously observe who, when, and where, we can describe the likely distributional impact of congestion charges, and provide insight into the marginal valuation of different types of trips.

We find that most reductions in driving come from low income drivers, particularly low income drivers who are not senior citizens. Most of the dropped trips are trips to shops and malls. Work commutes and school pick-ups and drop-offs are unchanged by the road use charges that we examine.

Finally, we show that under revenue-recycling the burden of congestion pricing does not fall on the poor or elderly. By knowing who responds, we are able to parse responsiveness by disadvantage, specifically income and limited access to public transport. We use our experimental estimates of price elasticity to show that policies that partially replace fuel and registration charges with road use charges lead to increases in consumer surplus for low-income households.

To our knowledge this paper is the first to use GPS transponders to study how individuals respond to road pricing. The paper with the closest level of detail is Bento et al. (2017), which has individual-level data on all Express Lane trips and tolls paid, but only for the subset of drivers who have opted onto the tolled road, when they are on the tolled road.

It is also one of the first studies with experimentally-allocated road use charges. A parallel paper, Kreindler (2018), provides car and motorbike commuters in Bangalore with incentives to avoid starting commutes at peak times and monitors compliance via a smart phone app. The author develops a research design that allows him to estimate how much individual drivers value their time and being on time, and make predictions that include a general-equilibrium response. Our paper differs primarily in that we look at a wealthy country, and observe all the trips that a household makes.

The experimental variation in cost from our experiment also allows us to contribute to the literature on gasoline demand, which has struggled to find good instruments for fuel prices (Hughes, Knittel, and Sperling (2008), Gillingham et al. (2015), Coglianese, Davis, Kilian, and Stock (2017), Levin et al. (2017)). Defining the marginal cost of driving as the product of fuel prices and vehicle fuel economy, our experimental variation doubles the average per-kilometer cost of driving in our sample. We find a mean short-run price elasticity of -0.13, which is consistent with the literature on short-term demand response to gasoline price increases. The price elasticity of demand for road use is a key input into transport infrastructure planning, government revenue forecasting, and the evaluation of policies to tackle the growing problems of pollution and road congestion.

Finally, this paper contributes to the literature on the welfare effect of transportation charges. Previous papers rely on cross-sectional variation in prices and reported driving from the Consumer Expenditure Survey (CES) (West and Williams (2004)) or, for new vehicles, detailed smog-check odometer data and postcode-level incomes (Gillingham (2014)). We explore heterogeneity along gradients of income and access to public transport using household-specific income and age and GPS measures of road use. We similarly find that low-income households are more price elastic, which mitigates the loss in consumer surplus associated with higher per kilometer charges.

The paper proceeds as follows. Section 2 describes the MRUS experiment and Section 3 presents baseline data. Section 4 asks to what extent discretionary trips take place under congested road conditions. Section 5 studies who wins and loses under road use charges. Section 6 presents some robustness tests and Section 7 concludes.

2 The experiment

The Melbourne Road Use Study (MRUS) was conducted by Transurban with the help of a team of industry partners in charge of conducting the randomization, installing the GPS devices, collecting and processing the data, sending out invoices, and interacting with households. The experiment was rolled out progressively starting in November 2015, with the latest participants starting in April 2016. For the average household the experiment lasted 9 months: three months of baseline driving followed by three months of the first treatment and then two months of the second treatment, with a few untreated weeks in between and afterwards. Recruitment date was randomly assigned.

Melbourne is similar to the Greater Boston metropolitan area in population (4.8 million inhabitants). It is similar to the Greater Los Angeles area in population density (1173 people/mi^2). Gasoline prices are US $4/gallon – higher than prices in Boston or San Francisco, but much lower than prices in London. The TomTom Traffic Index ranks Melbourne, Australia as the 58th most congested city in the world, on a par with Singapore and not far below New York City and Seattle.[3]

Figure 1 in the Appendix shows that across Melbourne there is important variation in both income and access to public transportation. Public transit takes the form of commuter rail, tram, and bus. For our analysis, we focus on access from rail and tram stations.

Participants were randomly selected from three geographical zones within the Greater Melbourne region. To make the study representative of the local population, the study sample was determined using stratification and a household cluster design.[4] Targeted households were recruited via in-person interviews. All participants were provided a $100 gift card on joining the study. Upon recruitment, GPS devices were installed in each household's primary vehicle. When a household had multiple vehicles, the GPS device was installed in the newest vehicle. These devices collected geographical coordinates at a fine level of spatial resolution at six second intervals whenever the vehicle was in motion. A privacy cordon was applied to an area around participants' homes concealing the GPS coordinates whenever the participant's device was inside the cordon. The radius of the privacy cordon varies based on population density; it is typically a few blocks.[5]

After several months of baseline travel, 1026 households were randomly selected for price treatments from the sample of participants. A control group of 356 participants did not experience any road charges. There were two rounds of charges. In the second phase treated households were randomly allocated to one of two pricing plans: either a per kilometer charge that varied by time-of-day, or a uniform per kilometer charge coupled with a cordon charge (a charge for entering a well-defined location).

In the first round, although selection of the treatment group was random, treated households were offered the option of one of three other pricing treatments (trip-based, uniform VMT, or flat rate). We discuss the sub-treatment selection in this phase and how we account for it in sections 3 and 6.1,

[3]`http://www.tomtom.com/en_gb/trafficindex/`

[4]Household selection was restricted to Statistical Area 1s (SA1s) with greater than 120 dwellings. Ninety SA1s were targeted for recruitment with a further 30 identified and held in reserve in case of non-response. Statistical Areas are defined by Australian Statistical Geography Standard as used by the Australian Bureau of Statistics

[5]This paper exclusively uses the centroid of the SA1 in which the household is located as a proxy for the home location. The median SA1 in our sample is approximately 400 meters wide. The mean SA1 is 515 meters wide. There are only 12 households in SA1s that are over two kilometers wide, i.e. where measurement error may be relevant to our household classifications; these SA1s are all located over 40 kilometers away from the CBD, placing them in the top 90th percentile of distance from the CBD.

respectively. Each sub-treatment had a limited number of slots, so households that were recruited later had fewer options.

The uniform VMT treatments in the first phase were priced at 10 cents per kilometer. The per trip plan was priced at $1 per trip,[6] The 'flat rate plan' applied no charge for household i's first X_i kilometers, where the number of free kilometers allocated each month was calculated based on baseline use. Households were charged 20 cents per kilometer for all kilometers exceeding that threshold. The time-of-day plan applied 15 cents per kilometer Monday to Friday 7am-9am and 3pm-6pm and 8 cents per kilometer at all other times. The distance plus cordon plan applied 8 cents per kilometer anytime plus $8 access charge per day to enter or move within a defined inner-city zone Monday to Friday 7am-6pm. The defined inner city zone corresponds to an expanded zone around Melbourne's Central Business District (CBD) and is shown in Figure 2. All charges applied to all driving, not just driving on toll roads.

The treatments were applied via a system of travel credit accounts. Travel account opening balances were calculated based on each participant's baseline road usage and their allocated treatment plan. As a treated household used their vehicle, road charges were deducted from their travel account. Households that reduced their road use relative to their baseline levels received a credit, up to a maximum of $80 per month. Households that increased their relevant use relative to baseline in a given month were not penalized. Every month participants received an invoice detailing the accumulated balance in their account. Households also had the option of accessing their balance in real time via a web portal. The final balance was paid out at the end of the study.

Two types of in-vehicle GPS devices were used in the study. Most participants received an OBD-II (On-Board Diagnostics - Second Generation) GPS device that is plugged into an OBD port, usually located under the dashboard. Once installed, the device is not generally visible to the driver. Older vehicles, that did not have an OBD port, received a plug-in GPS device which included a power cable, installed via the vehicle's dashboard accessories port and a GPS antenna, placed on the dashboard for best reception. Seventy-one percent of the vehicles in the study were eligible for the OBD device.

3 Data

Our primary source of data is anonymized driving data and household surveys from the MRUS. The GPS data that we received includes 43 million location coordinates and time stamps, representing readings taken every 6 to 30 seconds. All observations within each household's privacy cordon were masked. The GPS devices never recorded instantaneous speeds. All reference in this paper to speed refers to implied average speed determined through processing of location and time data.

We discarded a very small fraction of the total number of observations in creating our sample. We dropped all driving that took place outside of the state (closest border is over 200 kilometers away from Melbourne).[7] We also dropped trips with average speeds of less than 1 kilometer per hour, trips that reported stop times before start times, and observations with time stamps that implied average trip speeds that exceeded 200 kilometers per hour. Finally, we dropped treatment households that attrited during

[6] Vehicle movement is defined as a trip if the vehicle travels more than 100 meters after being stopped for at least five minutes.
[7] This is the largest restriction, which affected 10,879 trips out of a total of over 1.2 million trips. Our main results are not affected by this restriction.

the baseline period and control households that attrited before 1 May, 2016.[8]

In order to estimate price elasticities we combined the MRUS vehicle make and model with fuel economy data from the Australian government's Green Vehicle Guide (GVG) and the Department of Environment's Fuel Consumption Guide Database 1986-2003.[9] We also incorporated monthly fuel price data from the Australian Automobile Association (2017).

Tables 1 and 2 present household and baseline trip characteristics for treatment and control groups. To facilitate comparison, we contrast our sample averages to the 2008 summary statistics of the 100 largest Metropolitan Statistical Areas (MSAs) in the United States calculated by Couture et al. (2017). Melbourne drivers in our sample take slightly fewer trips per day (3.3 trips per day instead of 4.1 in the large US cities) which cover slightly shorter distances (9.9 kilometers per trip instead of 12.8) but at slower average speeds (33.2 kilometers per hour relative to 38.5), so average trip duration is slightly shorter (16.4 minutes per trip instead of 17.5).

Figure F.1 shows the distribution of some key variables. The typical household spends 20-30% of their travel time driving at peak times, with a few households spending over 80% at peak (Panel (c)). Most households in our sample live within 10 kilometers of a commuter rail station; 75% live within 4 kilometers, 46% of households live within walking distance (20 minutes for 1km = 0.6mi) and 22% live within 10 minutes (500m). The typical household has a vehicle with a fuel economy ranging from 7 to 10 liters per 100 kilometers, or 23.5 to 33.6 miles per gallon, similar to the on-road ratings for 2017 Subaru Outbacks and Honda Civics.

One of our metrics as to whether road use charges are likely to reduce congestion is if they reduce the number of trips taken on Melbourne's most congested roads. To this end we obtained maps of Melbourne's road network from the Department of Environment, Land, Water & Planning and took note of all driving on the 25 most congested roads as identified by Austroads 2016. These roads include four expressways and 21 local or arterial roads. The map of the roads is shown in Figure F.3 in the Appendix. During the baseline, 11% of all kilometers driven were on these roads.

It's important to note that in Melbourne it is not just the expressways that are congested. Figure F.4 reports the average speeds that we observe for all baseline trips on the most congested roads in Melbourne. We see that there is significant congestion on local roads and arterial roads as well. The big difference is that freeway congestion is much more predictable: it's concentrated during the morning and afternoon peaks (7-9am and 3-6pm). Congested local and arterial roads can be congested almost any time, often also in the middle of the day and in the evening. Figure F.5 shows a distribution of speeds (accumulating speeds over 30 second-intervals while on those roads) by time of day and weekday vs. public holiday. We note that congestion is not restricted to the inner city area or peak times, although it is clearly worse in those locations and at those times. Also, congestion, as evidenced by travel at low speeds, occurs primarily at peak times on the congested expressways, but spreads into midday and evening times on the local and arterial roads.

To classify trips by destination, we obtain shape files for points and features of interest, commuter rail

[8] Most of these households attrited within a few days of installing the GPS devices and were replaced by other randomly-sampled households in their SA1. The treated households that attrited while in the baseline period had not yet been informed that subsequent phases would include road use charges.

[9] These are available online at `https://www.greenvehicleguide.gov.au/` and `http://www.environment.gov.au/settlements/transport/fuelguide/search.html`.

parking lots, and school zones from the Victorian Government. We also obtain zoning data that allows us to confirm when drivers enter special use zones, like shopping malls, national parks, and airports. Finally, we use Google Places to identify all shops and other places of interest within 50 meters of where drivers park their vehicles. We develop algorithms on timing and destination frequency to identify trips that are work commutes, even those that do not occur during regular business hours. Appendix C describes in detail how we identified work commutes and classified trips by destination type. We then create driver profiles based on driving patterns, both using categories common in the transport literature and letting the data tell us what heterogeneity matters using a factor-analysis approach.

Table 1 shows that the treatment and control groups are balanced in the aggregate. One exception is distance to public transit; on average, households treated in the second phase lived one kilometer closer to train or tram stations than the control group, which lived 3.8 kilometers away. Table 2 shows that the randomly-allocated congestion-based sub-treatments in the second phase of the experiment are also balanced between sub-treatment and control groups. The individual sub-treatments in the first phase, however, show significant differences when compared to the control group because participants opted strategically into the treatment plans offered in this phase. Specifically, households that took longer trips and traveled more each day were more likely to prefer and get allocated to the trip-based charge. Households in the flat rate sub-treatment and, to a lesser extent, the distance charge sub-treatment, live closer to the CBD and took shorter trips during the baseline period.

4 How do drivers respond to road use charges?

4.1 Empirical strategy

In many ways, the MRUS was a traditional RCT. It differed, however, in one important way. In the second phase, treated households were randomly allocated to time-of-day and cordon charges. But in the first phase, although treatment was randomized, treated households were allowed to choose among three types of sub-treatment, subject to availability. This round involves the per kilometer distance charge, as well as a per trip charge and flat rate plan. We deal with sub-treatment selection in the first phase by modeling the selection process and recreating it for the control group, which was not asked to rank preferences. We create inverse probability weights for this selection into phase one sub-treatment and present all results for the uniform VMT treatment from regressions using these weights. Intuitively, the weights help us compare each treated subgroup to a subset of the control group that is likely to have similar sub-treatment preferences. This procedure is described in more detail in section 6.1. We find that our weighted results change very little relative to unweighted regressions, especially those that control for baseline covariates or household fixed effects (Table E.1).

We estimate average treatment effects in a difference-in-difference framework that is robust to treatment effect heterogeneity, following Imbens and Rubin (2015)'s recommended regression-based estimation with covariate adjustment. For each treatment, the regressions take the form:

$$y_{it} = \alpha + \beta \text{Treatment}_{it} + \left(\mathbf{X}_i - \overline{\mathbf{X}}\right)\gamma + \left(\mathbf{X}_i - \overline{\mathbf{X}}\right) \times \text{Treatment}_{it}\, \delta + \epsilon_{it}$$

where y_{it} is average daily kilometers traveled, trips taken, minutes spent driving, or number of destinations by household i on date t. We include GPS data from the baseline and treatment periods. All variables are demeaned by date. *Treatment* is an indicator variable that takes on a value of 1 if household i is treated on date t and 0 if not. Each sub-treatment is estimated separately relative to the entire control group. $\mathbf{X}_i$ is a vector of household-specific pre-treatment covariates, including average daily values for y_i during the baseline period, whether the primary driver is 65 years or older, whether that driver is employed, whether the household has an income below $65,000, whether the household includes children, and whether the home is located more than 1km away from public transport (train or tram). β is the average treatment effect and δ is a vector of coefficients representing the heterogeneity of the treatment effect.

For robustness, we also estimate all of the regressions using household and date fixed effects:

$$y_{it} = \alpha \text{Treated}_{it} + \mu_i + \tau_t + \epsilon_{it}$$

where μ_i are household fixed effects, τ_t are date fixed effects. The results are very similar, in both magnitudes and statistical significance.[10] In all specifications we cluster standard errors at the household level.

To facilitate comparison with the literature, we also present our results as estimates of the per kilometer price elasticity of road travel, specifically vehicle-kilometers traveled as a function of per kilometer cost. We calculate each household's baseline travel cost as the per kilometer cost of fuel: the fuel economy of their vehicle in liters per kilometer multiplied by monthly average fuel prices. We follow the standard in the literature (Gillingham (2011)) but note that this measure does not include wear and tear, insurance, or time costs. During treated months we add 10 cents per kilometer for all charged trips for the distance-based charge, 8 cents (off-peak) or 15 cents (peak) per kilometer for the time-of-day charge. As shown in Figure 3, experimental variation of 10 cents per kilometer doubles the average per-kilometer cost of driving in our sample.

Because this measure of travel cost is a function of vehicle choice we have potentially introduced price endogeneity. We instrument for travel cost using a dummy variable that equals 1 for treated units once treatment has started. We thereby identify the price elasticity based exclusively on price changes induced by the experiment. We estimate via two-stage least squares:

$$\log(q_{it}) = \eta_k \log(\text{travel cost}_{ikt}) + \mu_i + \tau_t + \epsilon_{it} \tag{1}$$

where η_k is the price elasticity of kilometers traveled with respect to the per kilometer cost of driving under treatment k, μ_i are household fixed effects, τ_t are week fixed effects, and ϵ_{it} is a residual error term. We again cluster standard errors at the household level.

For the elasticity regressions we aggregate driving data from the daily to the weekly level because there are many days (27% of all household-days in our sample) on which households do not drive at all. Taking the log of those daily zeros would drop them from the regression and make any results conditional on driving. At the weekly level only 6% of household-weeks involve no vehicle use, and are not included in the estimation. These weeks are likely to represent holiday absences.

[10] As a further robustness, we estimate the cordon and time-of-day treatments using random effects. Again we find very similar results.

4.2 Uniform VMT charges

Panel (a) of Table 3 presents the effect of the constant per-kilometer charge on daily trips, distance traveled, and time spent traveling. When charged an additional 10 cents per km, households drive 2.488 fewer km per day. On average households travel 33 km per day, so the increase in cost of driving translates to an 8% reduction in kilometers driven. The time spent driving decreases by over 4.24 minutes per day, representing a 6% reduction.

Table E.2 in the Appendix explores the source of this reduction. Under the distance-based charge, we note that about half of the reduction in distance traveled comes from an increase in the number of days with no driving at all (difference in treatment effect between Column (1) and Column (2). The other half of the reduction comes from motorists being more strategic with their time on the road, linking destinations together. We note that the reductions conditional on driving at all on a given day are not associated with a reduction in the number of destinations (Column (4)) or by a shift to closer destinations (Column (5)).[11]

As shown in the first column of Table 3 Panel (b), this reduction in driving corresponds to a price elasticity of kilometers traveled with respect to the per kilometer cost of driving of -0.13. In order to understand whether these reductions lead to improvements in traffic congestion, we first disaggregate the reduction in time spent driving by peak and off-peak road use and day of week. Panel (c) shows that the reductions are coming primarily from off-peak use, and trips that are not work commutes. Almost 3/4 of the reduction in distance occurs at off-peak times.

We further explore the peak/off-peak nature of the reductions by parsing the results by time of day, for weekdays and weekends. We allocate trip segments to the times at which they take place and regress hourly distance traveled on treatment, with a separate fixed effect for every hour of every day and household fixed effects by hour of day. Figure F.6 presents the results. The dotted red lines demarcate the beginning and end of peak road use times. Red diamonds indicate reductions that are significant at the 95% confidence level. We note that reductions are distributed between 8am and 8pm during the weekday, and noon to 2pm on weekends, with most statistically-significant reductions in the middle of the day and early evenings.

One way to measure congestion is by the speed at which cars are moving. We therefore ask whether the reductions lead to reductions in time spent in congested traffic, i.e. at low speeds. Figure 4 presents results parsed by driving speed. To create these graphs we allocated each trip segment between GPS readings to a corresponding vehicle speed vigintile.[12] We then aggregate the distribution of time spent in the vehicle at each speed for each household on each calendar date. We run regressions of daily time spent traveling, in minutes, on treatment status with a separate fixed effect for speed category on each day and household fixed effects by speed category. Average speed is determined through processing of location and time data; the GPS devices never recorded instantaneous speeds.

We find that, with the exception of some small reductions at very low speeds, the bulk of the reductions

[11] We show no evidence of a systematic change in destination location by regressing the daily sum of as-a-bird-flies distances between each destination and home on treatment status.

[12] We drop all almost-zero-speed readings at the beginning and end of each trip, representing time spent starting and stopping or parking the car. We keep all zero speed readings over the course of the trip, which could represent waits at traffic signals or gridlocked congestion.

from a simple per-kilometer charge come from relatively high speed micro-segments. In the US, the average speed during congested road use is 14.4 kilometers per hour (Cookson and Pishue (2017)). With per km charges, drivers primarily spent less time traveling at speeds of 35 to 75 kilometers per hour, with the largest reductions coming from trip segments traveled at 50 to 75 kilometers per hour.

4.3 VMT charges that vary by time-of-day

We then estimate the treatment effects for the distance by time-of-day charges. As shown in Table 4 Panel (a), the time-of-day charge led to fewer trips, but smaller overall reductions in distance and duration. Breaking down the reduction in travel duration, Panel (c) shows that most of the reduction occurs at peak times, contrasting with the results from the simple distance-based charges. Furthermore when we look at the reduction in distance traveled by hour of day (Figure **??**) we see that the largest and most significant reductions occur during the afternoon weekday peak. There is no strong evidence of substitution to off-peak times, with minor (insignificant) increases observed only on weekend afternoons.

Table E.3 in the Appendix shows that whereas the distance-based charge did not significantly reduce driving on the Top 25 most congested roads, the reductions under this plan do. Travel on the most congested freeways is unaffected, but there is a reduction in driving on local highly-congested roads.

We now also find clear evidence of reductions in driving at lower speeds. Figure **??** shows significant reductions in driving at very low speeds below 20 km per hour.

The price elasticity of demand associated with the time-of-day charge is -0.09 for peak use and -0.08 overall (Panel (b)). Neither of these is statistically-different from zero. The daily reduction in peak use is small relative to the dramatic experimental increase in per kilometer cost of driving at peak times.

4.4 VMT charges + cordon charge

We then estimate the treatment effects for the distance plus cordon charge and present the results in Table 5. Under this treatment we see a much stronger demand response than for the other two treatments in the number of trips, and duration decreasing by around 10% (Panel (a)). However, as with the distance-based charge, Panel (b) shows that over 80% of the driving reduction occurs in off-peak trips that are not workplace commutes. While in the aggregate off-peak trips are being reduced, we do see a significant reduction early in the afternoon peak period on weekdays as shown in Figure **??**. We also find that drivers are spending less time driving at all speeds below 55 km per hour (Figure **??**).

We then look to see to what extent the cordon charge led to reduced entry into the cordon. We restrict our sample to the households that ever entered the cordon during the baseline period. 40% of households never crossed into the cordon at relevant times. We find that, on average, the reduction in entry is not statistically-significant. The only reduction in cordon entry that we observe is among households that live more than a half a kilometer but less than a kilometer from public transit (Table **??**). This evidence is consistent with households being willing to walk to access public transit increases with the higher charges.

In Table 5 Panel (c) we check for spillovers into the border and in a larger ring around the priced inner cordon. We see noisy reductions in driving along the border and an increases in driving in the outer ring. We note that baseline traffic in the cordon, border, and outer ring are particularly peaky compared to average road use patterns (Figure F.7) Yet we do not find any evidence of substitution to unpriced times under the cordon charge; we actually find a large reduction in cordon entry on weekends, which were unpriced. It is possible that because of the salience of the cordon map provided to households, they focused on the geography rather than the timing of the treatment.

4.5 What trips do they reduce?

We then turn to the types of trips that households take. Figure 6 shows road use broken down by destination. The largest number of kilometers is associated with trips to shops. We divide shopping trips into two categories: locations that involve one of the three largest grocery store chains ("grocery" trips), and destination that do not ("other shops"). Table **??** shows the breakdown by number of trips and driver profile.

We then re-estimate the model separately for each category of destination, focusing on the kilometers driven for each destination. We present the results for the time-of-day VMT and uniform VMT plus cordon in Table **??**, showing the coefficients on all of the heterogeneous interactions. Figure 6 shows the coefficients for the main treatment effect by destination for each of the road charges. Across the board, we observe reductions in drives to shops, and to a lesser extent, less driving to parks. There is no change in school trips and work commutes.

There are two potential implications of the shopping result. First, it shows relatively low valuation for additional shopping trips, which may represent that it is easy to stock up. The average household takes 10 trips every week to locations that have a grocery store and 4 trips/week to locations with other shops. It could also be evidence of leakage. Melbourne has a well-developed system for online grocery shopping. If households are ordering groceries, they are potentially adding distance onto truck routes, which has an environmental cost, and may have a congestion cost.

5 Distributional impacts

We begin by describing the drivers in our sample by reported income. Households directly provided a census category measure of gross annual income in the recruitment survey. Our measure of household income includes pensions and government transfers. We define low income as below 65,000 AUD, or 51,636 USD. This value equates to the 40th percentile of gross income in Australia.[13]

Table 8 presents summary statistics by income. Low income households indeed live further from the downtown and further from public transit. But the difference is not large, and there is a lot of heterogeneity in both groups. In total, 41% of low-income households live within 1km of PT (18% within 500m) whereas 49% of higher incomes live that close (25% within 500m).

Households that live far from the CBD drive longer distances. On average, an additional 10km from the CBD leads to an additional 3.7 km driven per day. But low-income households are also much more likely to be over the age of 65, and seniors drive much less (25 km/day relative to 36 km/day for non-seniors). They also drive less at peak, and are less likely to drive into the center of town. In our sample,

[13] Median income was around $84,000 in 2015/16. `http://www.abs.gov.au/ausstats/abs@.nsf/mf/6523.0`. It was not possible to parse by above and below median income. We do not currently attempt to adjust household income by household size.

56% of low-income are seniors whereas 25% of higher income households are seniors. The net effect is that lower income households drive *less* than higher income households, conditional on driving at all.

Low income households also make up a relatively small share of the drivers in the congested downtown area. Table E.4 shows that households making less than $65,000 per year make up 30% of the household weekdays in our sample, but less than 15% of the cordon entries. Most cordon entries are from drivers from high income households that live far from the CBD and households that live close to the cordon (which is a predominantly high-income area).

Finally, across all low-income households, although vehicles are indeed older, vehicle footprint is on average smaller, so Table 8 shows that average fuel efficiency is only slightly worse.

5.1 Expenditures under different charging plans, assuming no demand response

We start our analysis by looking at how much drivers pay under the current system. Fuel taxes and vehicle registration fees make up a large component of transport-related charges in Australia. We estimate how much these expenditures would change for each income group under the distance-based, time-of-day distance, and cordon distance charges applied in our experiment, assuming that fuel taxes are replaced and the reduction of vehicle registration fees is calibrated to make the charges revenue-neutral in the aggregate. Table 9 presents the resulting change in weekly expenditures on transportation. These results are based on baseline driving data, i.e. under the scenario where there is no demand response. We find that the low-income households benefit from any of the three forms of road pricing that we consider if they replace existing user charges. This comes from low-income households driving less than higher income households. Low-income households are, on average, losers under the current system. 65% (75%) of households in the low (lowest) income categories would be better off under road use charges that are based on distance, 66% (76%) better off on time-of-day distance, and 69% (77%) better off on cordon plus distance charges. The percentages of those who would be better off are high, but the individual gains are small, on the order of $3 to $5 per week on average.

There is of course heterogeneity among these groups. Figure 7 shows the distribution of gains and losses across all households in our sample. Although the lower incomes have more households that gain (reduction in expenditure, to the left of zero in the figure) there are also households that lose (increases in expenditure, to the right of zero). We note however that there are very large losses larger than $20 per week, and those come from middle to higher income households. Also, these calculations still assume no demand response. Any demand response would mitigate the increase in expenditures, albeit at a cost of increased inconvenience.

In Figure 8 we split the heterogeneity by income and distance to public transport. The number of observations is relatively well balanced across cells, with slightly more observations in the upwards diagonal. We see that the increases in expenditures are indeed coming from households that are further from public transport, particularly households in the higher if not highest income groups.

To be even more specific, in Table 10 we present comparative statistics of the 4.7% of households in our sample that would stand to lose more than $20 per week if they faced new prices without changing their driving behavior. As expected, this subset drives further and more often. It also drives twice as much in the inner city. We also note that this sample is wealthier, more likely to be employed, and more likely to have a newer car.

5.2 Who responds to road prices

We then use the experiment to estimate the price elasticity of road use separately for each income group. Table E.5 presents results. For distance-based charges, we find the greatest price responsiveness among low-income households, consistent with West (2004) and Wadud et al. (2010) who evaluate the regressiveness of gasoline taxes. Table E.6 shows the price elasticity of low income households broken down by age, employment status, and access to public transport. We find no evidence of responsiveness among the elderly or the unemployed: the low-income responsiveness is driven by households where the primary driver is under the age of 65 and employed.

Using these estimated price elasticities, we then estimate the short-run change in welfare associated with different road use charges assuming constant elasticity of demand with respect to travel cost for each income group. Our welfare calculations are similar to those in Borenstein (2007). Under constant elasticity of demand, $q = \alpha p^{\eta}$, the change in consumer surplus, ΔCS, can be expressed as:

$$\Delta CS = \int_{p_1}^{p_0} p(x)dx = \frac{\alpha}{1+\eta}\left(p_0^{1+\eta} - p_1^{1+\eta}\right)$$

We allow α to vary at the household level i and η to vary at the income group level j. We estimate α_i and η_j using our experimental variation in price. Under peak/off-peak pricing we estimate separate α_{ih} and η_{jh} for each set of hours. Each household's consumer surplus is then the sum of its surplus from peak driving and off-peak driving.

We find consumer surplus increases by almost 4% for the lowest-income households when fuel and registration charges are partially replaced with road use charges. Table 11 presents our results. Column (1) shows percentage change in consumer surplus from road use charges with no compensation. Column (2) shows change in consumer surplus from road use charge assuming revenue-recycling. Under revenue-recycling the fuel tax is entirely replaced and annual vehicle registration fees are decreased by the amount needed to make the policy change revenue-neutral in the aggregate. We show results both under the assumption of constant elasticity across all income groups and taking into account the larger price responsiveness of lower-income groups. The price responsiveness mitigates the negative impact of an increase in charges and accentuates the positive impact of road use charges replacing existing charges. The greater increase in consumer surplus for low-income households comes from replacing current charges with road use charges that vary by time of day.[14]

We also do a similar analysis for access to public transit infrastructure. Table E.7 in the Appendix summarizes the treatment effects by distance to public transport. In this case we no longer find structurally-similar results across charge types. For the distance-based charge, we show in Table **??** Panel (b) that the largest reduction comes from among households that live both very close and very far to public transit. This result contrasts somewhat with Gillingham and Munk-Nielsen (2016), who find that the fuel price elasticity of driving demand is by far the highest both amongst households living in cities with very short

[14] Note that this analysis does not include the cost of implementing a system of road use charges. To the extent that a new system of collecting road revenues costs more than the existing system, less revenue would be redistributed.

commutes (as do we) and amongst households living in the outskirts of cities with long commutes but adequate access to public transport (unlike us). We check for evidence of households that are far from public transport increase their use of commuter rail by parking at or getting dropped off at rail stations. Although almost half of our sample is observed parking at or getting dropped off at a train station, we show in Table E.8 that there is no evidence that the charges led to changes along this margin.

In contrast to the distance-based charge, under the time-of-day and cordon charge, the reductions at peak times and in cordon entry come primarily from households that are 0.5 to 1 kilometer away from public transport, as shown in Table E.7 and Table **??**. This distance represents a 10 to 20 minute walk. Households that respond may be the ones that may live close enough to walk to public transport, but not so close that it was already their preferred mode of transport. It appears that the charges are pushing out the distance that households are willing to walk to access public transport.

6 Robustness and subtreatment selection in round 1

In this section we explain our empirical approach to address sub-treatment selection into the distance-based charge. We also show robustness to a few areas of potential concern. First of all, we check for within household substitution to unmonitored vehicles. Half of the households in our sample had more than one vehicle. We find that all of our results are robust to restricting our analysis to households that have only one vehicle. Secondly, because account balances were based exactly on individual historical use, many households depleted their credits at the end of each month of treatment. We show that our results are robust to restricting our analysis to fixed periods for which almost all households had positive credits. Finally, we look for non-random attrition. Attrition rates were very low in this experiment, and balanced across treatment and control groups.

6.1 How we control for sub-treatment selection in round 1

In phase one of the study, treated households were provided information on their baseline driving behavior (e.g. trips, km per day) and were then asked to rank their preferences for treatments A, B and C, where A is a trip-based charge, C only charges households who increase their use relative to historical levels, and B is the distance-based charge. Households were then given their preferred treatment, subject to availability. This selection potentially introduces bias into the results because households are likely to strategically chose a treatment that maximizes their expected monetary gain from the experiment.

That said, households were not told that they would receive baseline credits based on their historical use before they ranked their preferences. In fact, they were asked to rank based on a charge on all units, not just the inframarginal ones. The summary statistics in Table 2 suggest that households selected sub-treatments in the first round based on levels of historical use. Households picked plans that would make them better off under a tax, or "structural winners" under a subsidy where everyone received the same level of baseline credits. In practice, however, baseline credits depended on individual historical use, so households that traveled relatively few kilometers, who opted for a per kilometer charge, found themselves needing to further reduce kilometers in order to make a profit.

In estimating our treatment effect, we worry about bias in the other direction: selection on elasticity.

We would overestimate the treatment effect if households picked a plan based on the ease with which they anticipated they could make future reductions.

To address this potential bias we adapt the approach outlined in Imbens and Wooldridge (2009), which combines propensity score inverse probability weights with regression to estimate the ATE. We want to match treated households to control households with similar ranked preferences. Because we do not have data on control group preferences, we estimate them. Specifically, we run a multinomial logit model on all treated households that estimates the propensity $P_i(X)$ for household i to pick sub-treatment X as their first choice, as a function of pre-treatment household and trip characteristics. We see the full set of stated preferences for all treated households because options were not removed when they filled up. We then use control group household and trip characteristics and the regression coefficients from the multinomial logit to estimate the likelihood that each control household would have ranked each sub-treatment first. We use the inverse propensity scores to weigh observations in our treatment and elasticity regression models. Because our goal is not to predict treatment assignment across treatment and control groups, but rather to predict ranked preferences in order to compare households that are equally likely to have wanted the same sub-treatment, we weigh all units using the same formula. We weigh all treated units that received treatment B, regardless of whether or not B was their first preference, and all control units, by $1/P_i(B)$ where $P_i(B)$ is our estimated probability that B was household i's first choice.[15]

Table E.9 shows how household and trip characteristics in the pre-treatment period influence the likelihood that a household will rank a given treatment as their first choice. We see, for example, that holding all else equal at the mean values, an additional trip per day is associated with a household being 5 percentage points less likely to rank sub-treatment A as their first choice.

Figures F.8 and F.9 in the Appendix show good overlap in the propensity scores between treatment and control households with no extremely high or low values.

6.2 Substitution to unmonitored vehicles

Some households had the option of switching to unmonitored non-primary vehicles. Table E.10 shows that all of the results are robust to restricting the analysis to households that have only one vehicle. We would expect to see a very large price responsiveness among multi-car homes if households were substituting away from the monitored vehicle to unmonitored vehicles, but there is no evidence of that being the case. In fact, we find a higher demand elasticity for single vehicle households, which is consistent with our finding a larger demand response among households that reported lower incomes.

6.3 Price nonlinearity

Because account balances were based exactly on individual historical use, many households depleted their credits at the end of each month of treatment. Households could only earn positive balances, not incur a debt, at the end of each month. This effectively created an endogenous non-linearity in the cost of driving near the end of each month for households that did not change their behavior. Figures F.10 Panel (a) shows that most households maintain a positive travel account balance in the first 19, 24, or 27 days of

[15] Note that this differs from the practice of weighting all treated units by $1/P$ and all control units by $1/(1-P)$ where P is the estimated probability of treatment.

the month, representing 90%, 80%, and 70% of all households, respectively. Figure F.10 Panel (b) shows that our results are robust to restricting our analysis to fixed periods in all months for which all or almost all households had positive credits.

It might be surprising that households did not increase their driving once they depleted their balance, dampening our estimated treatment effect. We unfortunately cannot identify whether households were aware of the exact day when they depleted their balance.

6.4 Attrition

Attrition rates during the treatment phases of the study were relatively low. Non-random attrition during the treatment phases has the potential to introduce bias in our results if individuals choose to leave the study because of the treatment they received or the size of their travel account balance. Table E.11 shows percentage attrition rates during each phase of the study. By the end of phase one, the rate of attrition in the control group is 6 percent, compared with under 2 percent for the distance charge treatment. From the start to end of phase two, attrition is around 5 percent for the two treatment groups and 7 percent for the control group.

One concern would be that the few households that do attrit mid-experiment are those least likely to respond, i.e. those who have been earning the least from their virtual accounts. To address this concern we compare the previous months travel account balances for those who attrited in a given month with those who did not attrit. In Table E.12 we check the balances of those who attrit and find no evidence that attritors were being paid less. Figure F.11 shows there is a very similar distribution of previous month balances between the two groups. These results allay fears that results are inflated by systematic attrition from the study of households with low monthly balances.

7 Conclusion

Cost-reflective prices are becoming increasingly common in essential services such as electricity and water. However, most road revenues are collected from charges that are only indirectly related to road use and not at all related to each driver's contribution to traffic congestion. Almost half of the average annual road bill in Australia is made up of gasoline excise taxes, which are essentially per kilometer fees for which more fuel-efficient vehicles pay less per kilometer traveled. Most of the remaining road bill is composed of fixed annual vehicle registration fees, amounting to several hundred dollars a year, that are tied to vehicle ownership regardless of vehicle use, and provide no incentive to help mitigate congestion (Infrastructure Victoria, 2016).

Except for toll roads, which make up a small fraction of the road network, we don't direct road charges to people who are actually on the road, and rarely charge more for use in congested locations at peak times. Yet we now have the technology that can help us reward drivers who reduce congestion and understand who responds to price incentives and how.

In this paper, we analyze data collected from 1,400 drivers across Melbourne to see whether road user charging can change their behaviour in ways that ease congestion. We consider three simple road use charges that could potentially target congestion: distance-based charges, time-of-day charges, and distance plus cordon charges. We see that kilometer-based charges alone reduces driving under uncongested road conditions. On the other hand, we provide evidence that time of use charges reduce driving at peak times and at low speeds, and that cordon charges reduce driving at low speeds.

As described by independent government advisory body Infrastructure Victoria (2016), the current system of road usage charges puts a disproportionate burden on low-income households that live further from the city. We show that while road use charges do impact the poor disproportionately, conditional on owning a car, existing fuel taxes are even more regressive. Low income households drive less, especially at peak, and respond more. Our research indicates that despite opposition on the grounds of fairness, charges that better target congested times and places may actually be a more prorgressive way to charge for roads.

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A Tables

Table 1: Summary Statistics and Balance - by phase

	Control		Treated phase one		Treated phase two	
	mean/sd	obs	diff/se	obs	diff/se	obs
Household						
Household Size	2.75	343	0.040	1017	0.078	668
	[1.40]		(0.085)		(0.091)	
Has Children (=1)	0.35	342	0.026	1015	0.032	668
			(0.030)		(0.032)	
Distance home SA1 to CBD (km)	23.9	351	-0.43	1025	-1.18	673
	[16.6]		(0.97)		(1.01)	
Distance home SA1 to rail/tram (km)	3.72	351	-0.69**	1025	-1.03***	673
	[6.81]		(0.35)		(0.36)	
Vehicle						
Multiple Cars (=1)	0.50	346	0.0049	1024	0.014	673
			(0.031)		(0.033)	
Petrol (=1)	0.83	356	0.0019	1026	-0.0023	673
			(0.023)		(0.025)	
Average litres fuel per 100km	8.77	344	-0.023	1024	0.046	673
	[2.32]		(0.14)		(0.15)	
Visible GPS (=1)	0.28	356	-0.015	1026	-0.018	673
			(0.027)		(0.029)	
Trip						
Distance traveled (km/day)	31.8	356	1.10	1026	0.66	673
	[23.7]		(1.32)		(1.40)	
Trips taken (/day)	3.25	356	0.16	1026	0.084	673
	[1.82]		(0.10)		(0.11)	
Distance per trip (km/trip)	9.92	356	0.096	1026	0.18	673
	[5.02]		(0.30)		(0.32)	
Trip duration (min/trip)	16.4	356	-0.29	1026	-0.35	673
	[7.49]		(0.48)		(0.48)	
Average speed (km/hour)	33.2	356	0.75	1026	0.91*	673
	[9.16]		(0.51)		(0.54)	
Time spent traveling (min/day)	50.0	356	1.91	1026	0.85	673
	[29.2]		(1.69)		(1.80)	
Time traveling at peak (min/day)	18.2	356	0.063	1026	-0.44	673
	[13.3]		(0.78)		(0.83)	
Share of time spent driving at peak (%)	35.4	356	-1.37	1026	-1.53	673
	[15.2]		(0.90)		(0.96)	
Share of hh-days entering CBD cordon (%)	3.72	356	0.080	1026	-0.062	673
	[9.56]		(0.57)		(0.60)	
Share of households ever commuting (%)	40.4	356	1.66	1026	2.34	673
	[49.1]		(3.03)		(3.24)	
Average duration of commutes (min/day)	63.2	144	2.81	432	0.98	288
	[27.7]		(3.08)		(3.03)	

Notes: Mean value for the control group and differences in mean for the treated group in each phase relative to the control group. Standard deviations in square brackets, standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2: Summary Statistics and Balance - by treatments

	Control		Treated - Phase one						Treated - Phase two			
			Distance		Per trip		Flat rate		Time of day		Cordon	
	mean/sd	obs	diff/se	obs	diff/se	obs	diff/se	obs	diff/se	obs	diff/se	obs
Household												
Household Size	2.75	343	0.11	352	-0.093	338	0.11	327	0.087	342	0.070	326
	[1.40]		(0.11)		(0.10)		(0.11)		(0.11)		(0.11)	
Has Children (=1)	0.35	342	0.057	348	-0.013	337	0.031	330	0.028	343	0.037	325
			(0.037)		(0.037)		(0.037)		(0.037)		(0.037)	
Distance home SA1 to CBD (km)	23.9	351	-1.60	354	2.96**	340	-2.66**	331	-1.71	344	-0.62	329
	[16.6]		(1.18)		(1.27)		(1.18)		(1.19)		(1.20)	
Distance home SA1 to rail/tram (km)	3.72	351	-1.17***	354	0.40	340	-1.30***	331	-1.12**	344	-0.95**	329
	[6.81]		(0.43)		(0.50)		(0.44)		(0.45)		(0.45)	
Vehicle												
Multiple Cars (=1)	0.50	346	0.0014	353	0.027	340	-0.013	331	0.0087	344	0.020	329
			(0.038)		(0.038)		(0.038)		(0.038)		(0.039)	
Petrol (=1)	0.83	356	0.024	354	-0.031	340	0.012	332	-0.020	344	0.017	329
			(0.027)		(0.029)		(0.028)		(0.029)		(0.028)	
Average litres fuel per 100km	8.77	344	0.11	354	-0.12	339	-0.063	331	-0.030	344	0.13	329
	[2.32]		(0.18)		(0.18)		(0.17)		(0.17)		(0.18)	
Visible GPS (=1)	0.28	356	-0.041	354	0.010	340	-0.013	332	-0.022	344	-0.014	329
			(0.033)		(0.034)		(0.034)		(0.033)		(0.034)	
Trip												
Distance traveled (km/day)	31.8	356	0.49	354	4.52**	340	-1.75	332	1.31	344	-0.013	329
	[23.7]		(1.64)		(1.76)		(1.64)		(1.71)		(1.63)	
Trips taken (/day)	3.25	356	0.26**	354	0.050	340	0.16	332	0.11	344	0.060	329
	[1.82]		(0.13)		(0.13)		(0.13)		(0.13)		(0.13)	
Distance per trip (km/trip)	9.92	356	-0.52	354	1.73***	340	-0.92***	332	0.23	344	0.14	329
	[5.02]		(0.34)		(0.41)		(0.35)		(0.36)		(0.38)	
Trip duration (min/trip)	16.4	356	-1.25***	354	1.94***	340	-1.54***	332	-0.11	344	-0.61	329
	[7.49]		(0.47)		(0.74)		(0.48)		(0.60)		(0.51)	
Average speed (km/hour)	33.2	356	0.24	354	2.57***	340	-0.58	332	0.87	344	0.96	329
	[9.16]		(0.62)		(0.69)		(0.63)		(0.65)		(0.65)	
Time spent traveling (min/day)	50.0	356	1.47	354	5.13**	340	-0.93	332	1.63	344	0.042	329
	[29.2]		(2.06)		(2.21)		(2.10)		(2.16)		(2.07)	
Time traveling at peak (min/day)	18.2	356	-0.44	354	1.33	340	-0.70	332	-0.29	344	-0.59	329
	[13.3]		(0.95)		(1.03)		(0.95)		(0.97)		(0.98)	
Share of time spent driving at peak (%)	35.4	356	-2.01*	354	-1.43	340	-0.63	332	-1.37	344	-1.70	329
	[15.2]		(1.11)		(1.16)		(1.11)		(1.10)		(1.14)	
Share of hh-days entering CBD cordon (%)	3.72	356	-0.22	354	0.98	340	-0.53	332	0.29	344	-0.42	329
	[9.56]		(0.67)		(0.79)		(0.64)		(0.72)		(0.69)	
Share of households ever commuting (%)	40.4	356	0.51	354	1.32	340	3.23	332	0.54	344	4.23	329
	[49.1]		(3.69)		(3.74)		(3.77)		(3.72)		(3.78)	
Average duration of commutes (min/day)	63.2	144	1.22	145	11.6***	142	-4.17	145	2.64	141	-0.62	147
	[27.7]		(3.41)		(4.01)		(3.27)		(3.41)		(3.48)	

Notes: Mean value for the control group and differences in mean for each subgroup relative to the control group. Standard deviations in square brackets, standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Daily treatment effects under the uniform VMT charge

Panel (a): Daily treatment effects

VARIABLES	(1) Trips (/day)	(2) Distance (km/day)	(3) Duration (min/day)
Treatment = 10c per km	-0.0965	-2.055*	-2.951**
	(0.0748)	(1.060)	(1.304)
Observations	147,831	147,831	147,831
R-squared	0.0308	0.00541	0.0142
Treated hh	353	353	353
Control hh	356	356	356
Mean dep var	3.375	32.23	51.61

Panel (b): Elasticity of travel demand

VARIABLES	(1) Overall	(2) Peak	(3) Off-peak
log per kilometer cost of travel	-0.1213**	0.0112	-0.1024**
	(0.048)	(0.052)	(0.047)
Observations	19,692	17,940	19,420
R-squared	0.0252	0.0136	0.0192
Treated hh	353	353	353
Control hh	344	344	344
CDW F-test	10510	10144	10522

Panel (c): Time spent driving (minutes/day) by peak, day of week, and type of trip

VARIABLES	(1) Peak	(2) Off-peak	(3) Mon-Fri	(4) Weekend	(5) Commute	(6) Not commute	(7) CBD	(8) CBD ring	(9) Far CBD
Treatment = 10c per km	-0.882	-2.017**	-3.589**	-1.617	0.341	-3.292***	-0.345***	-0.328	-2.277**
	(0.572)	(0.855)	(1.535)	(1.378)	(0.537)	(1.219)	(0.127)	(0.214)	(1.156)
Observations	147,831	147,831	100,464	47,367	147,831	147,831	147,831	147,831	147,831
R-squared	0.204	0.00834	0.00931	0.0139	0.0684	0.00955	0.00338	0.00608	0.0130
Treated hh	353	353	353	353	353	353	353	353	353
Control hh	356	356	356	356	356	356	356	356	356
Mean dep var	18.70	28.03	54.11	46.29	8.451	43.16	1.351	3.600	46.66

Notes: The distance-based charge is 10 cents per kilometer. Each column header represents a different dependent variable. Panel (a) regresses the following on active treatment status: column (1): number of trips per day, column (2): kilometers per day, column (3): minutes traveled per day, column (4) number of destinations, not including home, each day. Panel (b) shows TSLS regressions of log price on log distance estimated via TSLS using active treatment status as an instrument for price. Price is the per kilometer cost of road use, including fuel costs and experiment charges. Distance is kilometers per week. In Panel (b) column (1) presents results for the full sample, column (2) restricts to peak trips, where peak is defined as Monday through Friday 7-9am and 3-6pm, and column (3) restricts to off-peak driving. Trips that span both peak and off-peak periods are proportionately allocated to each. In panel (c) the dependent variable is total time spent driving, in minutes per day. Panel (c) columns (1) and (2) restrict to peak and off-peak driving, respectively. For columns (3) and (4), Monday-Friday represents all weekdays that are not public holidays; weekends include public holidays. For columns (5) and (6) commuting trips are defined as repeated roundtrips to a common location for which a driver arrives between 6am and 10am on a non-holiday weekday and stays 5-15 hours. For columns (7) and (8) CBD refers to driving in the inner cordon any time. CBD ring refers to driving along the border of the inner cordon or in the outer cordon any time. Panels (a) and (c) also control for covariates, including mean value of dependent variable during baseline, and interaction between covariates and treatment. Panel (b) includes household fixed effects. Panels (a) and (c) demeans all variables by date; panel (b) includes week fixed effects. Regressions include inverse probability weights to address sub-treatment selection. Standard errors are clustered at the household level. hh = households. The bottom row shows the mean of the dependent variable for the control group and for the relevant treated group during pre-treatment baseline. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4: Daily treatment effects under the time-of-day VMT charge

Panel (a): Daily treatment effects

VARIABLES	(1) Trips (/day)	(2) Distance (km/day)	(3) Duration (min/day)
Treatment = 15c peak 8c off-peak	-0.250***	-1.660	-2.281
	(0.0836)	(1.104)	(2.028)
Observations	138,674	138,674	138,674
R-squared	0.250	0.183	0.153
Treated hh	344	344	344
Control hh	356	356	356
Mean dep var	3.315	32.06	51.40

Panel (b): Elasticity of travel demand

VARIABLES	(1) Overall	(2) Peak	(3) Off-peak
log per kilometer cost of travel	-0.0813	-0.1059*	0.0078
	(0.062)	(0.055)	(0.076)
Observations	18,320	16,697	18,069
R-squared	0.0286	0.0146	0.0220
Treated hh	344	344	344
Control hh	344	344	344
CDW F-test	8800	11675	9185

Panel (c): Time spent driving (minutes/day) by peak, day of week, and type of trip

VARIABLES	(1) Peak	(2) Off-peak	(3) Mon-Fri	(4) Weekend	(5) Commute	(6) Not commute	(7) CBD	(8) CBD ring	(9) Far CBD
Treatment = 15c peak 8c off-peak	-2.068***	-0.123	-3.267	0.314	-0.132	-2.062	-0.224	-0.408	-1.730
	(0.680)	(1.568)	(2.011)	(2.733)	(0.529)	(1.943)	(0.211)	(0.284)	(1.847)
Observations	138,674	138,674	94,942	43,732	138,674	138,674	138,674	138,674	138,674
R-squared	0.175	0.106	0.186	0.154	0.148	0.134	0.154	0.291	0.158
Treated hh	344	344	344	344	344	344	344	344	344
Control hh	356	356	356	356	356	356	356	356	356
Mean dep var	18.75	27.90	54.30	45.27	4.843	46.56	1.431	3.775	46.20

Notes: The time-of-day charge is 15 cents per kilometer during peak times and 8 cents off-peak. Peak is defined as Monday-Friday 7-9am and 3-6pm, off-peak is all other times. Each column header represents a different dependent variable. Panel (a) regresses the following on active treatment status: column (1): number of trips per day, column (2): kilometers per day, column (3): minutes traveled per day, column (4) number of destinations, not including home, each day. Panel (b) shows TSLS regressions of log price on log distance estimated via TSLS using active treatment status as an instrument for price. Price is the per kilometer cost of road use, including fuel costs and experiment charges. Distance is kilometers per week. In Panel (b) column (1) presents results for the full sample, column (2) restricts to peak trips, where peak is defined as Monday through Friday 7-9am and 3-6pm, and column (3) restricts to off-peak driving. Trips that span both peak and off-peak periods are proportionately allocated to each. In panel (c) the dependent variable is total time spent driving, in minutes per day. Panel (c) columns (1) and (2) restrict to peak and off-peak driving, respectively. For columns (3) and (4), Monday-Friday represents all weekdays that are not public holidays; weekends include public holidays. For columns (5) and (6) commuting trips are defined as repeated roundtrips to a common location for which a driver arrives between 6am and 10am on a non-holiday weekday and stays 5-15 hours. For columns (7) and (8) CBD refers to driving in the inner cordon any time. CBD ring refers to driving along the border of the inner cordon or in the outer cordon any time. Panels (a) and (c) also control for covariates, including mean value of dependent variable during baseline, and interaction between covariates and treatment. Panel (b) includes household fixed effects. Panels (a) and (c) demeans all variables by date; panel (b) includes week fixed effects. Standard errors are clustered at the household level. hh = households. The bottom row shows the mean of the dependent variable for the control group and for the relevant treated group during pre-treatment baseline. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Daily treatment effects under the VMT + cordon charge

Panel (a): Daily treatment effects

VARIABLES	(1) Trips (/day)	(2) Distance (km/day)	(3) Duration (min/day)
Treatment = 8c per km and cordon	-0.312***	-2.289**	-4.616***
	(0.0874)	(1.124)	(1.611)
Observations	136,039	136,039	136,039
R-squared	0.245	0.175	0.155
Treated hh	329	329	329
Control hh	356	356	356
Mean dep var	3.305	31.70	51

Panel (b): Time spent driving (minutes/day) by peak, day of week, and type of trip

VARIABLES	(1) Peak	(2) Off-peak	(3) Mon-Fri	(4) Weekend	(5) Commute	(6) Not commute	(7) CBD	(8) CBD ring	(9) Far CBD
Treatment = 8c per km and cordon	-1.187	-3.132***	-4.541**	-4.529**	0.00579	-4.637***	-0.372*	-0.184	-3.983***
	(0.753)	(1.007)	(1.795)	(1.843)	(0.561)	(1.484)	(0.217)	(0.280)	(1.444)
Observations	136,039	136,039	93,161	42,878	136,039	136,039	136,039	136,039	136,039
R-squared	0.182	0.103	0.190	0.156	0.144	0.134	0.132	0.288	0.159
Treated hh	329	329	329	329	329	329	329	329	329
Control hh	356	356	356	356	356	356	356	356	356
Mean dep var	18.67	27.59	53.67	45.35	4.841	46.16	1.336	3.542	46.12

Panel (c): Distance traveled (kilometers/day) in nearby areas or at other times

VARIABLES	(1) Inside cordon	(2) Cordon border	(3) Outer ring	(4) Mon-Fri 7am-6pm	(5) Mon-Fri off hours	(6) Sat-Sun any time
Treatment = 8c per km and cordon	-0.162	-0.0742	-0.0781	-0.0442	-0.0630	-0.0895**
	(0.132)	(0.117)	(0.180)	(0.0494)	(0.0504)	(0.0350)
Observations	43,358	43,358	43,358	66,227	66,227	66,227
R-squared	0.00588	0.00786	0.00750	0.0281	0.00961	0.0426
Treated hh	164	164	164	171	171	171
Control hh	153	153	153	160	160	160
Mean dep var	0.539	0.785	1.718	0.245	0.0869	0.130

Notes: The distance charge is 8 cents per kilometer. The cordon charge is $8 per day that the cordon is crossed. Peak is defined as Monday-Friday 7-9am and 3-6pm, off-peak is all other times. Each column header represents a different dependent variable. Panel (a) regresses the following on active treatment status: column (1): number of trips per day, column (2): kilometers per day, column (3): minutes traveled per day, column (4) number of destinations, not including home, each day. In Panel (b) column (1) presents results for the full sample, column (2) restricts to peak trips, where peak is defined as Monday through Friday 7-9am and 3-6pm, and column (3) restricts to off-peak driving. Trips that span both peak and off-peak periods are proportionately allocated to each. In panel (c) the dependent variable is total time spent driving, in minutes per day. Panel (c) columns (1) and (2) restrict to peak and off-peak driving, respectively. For columns (3) and (4), Monday-Friday represents all weekdays that are not public holidays; weekends include public holidays. For columns (5) and (6) commuting trips are defined as repeated roundtrips to a common location for which a driver arrives between 6am and 10am on a non-holiday weekday and stays 5-15 hours. For columns (7) and (8) CBD refers to driving in the inner cordon any time. CBD ring refers to driving along the border of the inner cordon or in the outer cordon any time. The dependent variables in Panel (c) columns (1)-(3) are distance traveled in each zone, in kilometers per day. The three zones, cordon, border, and outer ring, are shown in Figure 2. The dependent variables in Panel (c) columns (4)-(6) is the distance traveled in the inner cordon at the designated time. The sample for all regressions in panel (c) is restricted to treated and control group households that ever entered the inner cordon during the baseline period. The sample for columns (1)-(3) is further restricted to relevant days: Monday-Friday. All regressions control for covariates, including mean value of dependent variable during baseline, and interaction between covariates and treatment, and demean all variables by date. Standard errors are clustered at the household level. hh = households. The bottom row shows the mean of the dependent variable for the control group and for the relevant treated group during pre-treatment baseline. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Trips per week by destination and driver profile (level and % difference)

Destination	Employed		Not Employed	
	PT close	PT far	Seniors	Under 65
	per week/sd	% diff	% diff	% diff
Residential	2.06 [1.98]	3	-16**	19**
Grocery	10.7 [5.97]	0	-6	10**
Other shopping	4.82 [3.70]	5	-12**	-6
Park	1.03 [1.45]	2	13	25*
Sports	0.17 [0.64]	20	31	-33
Rural	0.14 [0.49]	29	35	-8
School	1.02 [2.23]	5	-91***	76***
Hospital	0.17 [0.63]	30	-8	-32
Elderly	0.28 [0.84]	-16	2	-2
Airport	0.071 [0.20]	-44***	-72***	-57**
Petrol Station	0.26 [0.29]	56***	3	41***
Work Commute	2.17 [3.16]	19**	-100***	-100***
Train Station	0.24 [0.88]	8	-79***	-47
During work	0.093 [0.35]	88*	-95***	-97***
Dropoff loop	1.31 [1.65]	53***	15	63***

Notes: First column presents average number of trips per week for employed drivers that live within walking distance (1 kilometer) of public transport (train or tram), standard deviation of the mean in brackets. For the three other categories of drivers, % difference in average weekly trips is shown. Stars represent the probability of observing the given data if the true mean difference in levels is zero. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Weekly treatment effects by destination and driver-type

Panel (a): Under cordon charge (kilometers/week

VARIABLES	(1) Residential	(2) Grocery	(3) Other shop	(4) Park	(5) Sports	(6) Rural	(7) School	(8) Hospital	(9) Elderly	(10) Airport	(11) Petrol	(12) Commute	(13) Train	(14) For work	(15) Loop
Treatment = 8c per km and cordon	-2.303	-8.093**	-6.984***	-2.670**	0.933**	0.510	-1.544*	-1.925***	-0.0106	0.622	-0.568	2.517	-0.183	-0.125	-0.683
	(1.557)	(4.088)	(2.517)	(1.198)	(0.364)	(0.866)	(0.870)	(0.527)	(0.438)	(0.521)	(0.598)	(2.699)	(0.302)	(0.384)	(0.476)
Treatment X Employed: PT far	-0.651	0.118	-0.334	1.295	0.0276	-2.069	0.952	0.314	-0.408	0.0772	1.175	10.13*	0.00385	-0.179	0.853
	(2.353)	(7.472)	(4.168)	(1.756)	(0.642)	(1.664)	(1.771)	(0.637)	(0.809)	(0.639)	(0.955)	(5.940)	(0.444)	(0.525)	(0.710)
Treatment X Not Employed: senior	-1.505	-2.344	-3.157	3.570	-0.888	1.439	-0.0355	-0.488	-0.332	-0.669	0.723	1.064	-0.396	-0.530*	-0.661
	(2.748)	(6.554)	(3.899)	(2.185)	(0.765)	(2.236)	(1.193)	(0.679)	(0.926)	(0.683)	(1.030)	(3.986)	(0.399)	(0.272)	(0.585)
Treatment X Not Employed: under 65	4.091	4.802	0.364	0.259	0.840	-3.002	-0.863	0.162	-1.182	0.0857	0.593	0.808	-0.499	-0.550**	-0.655
	(4.998)	(9.772)	(5.006)	(2.119)	(1.436)	(1.950)	(1.932)	(0.560)	(1.163)	(0.862)	(1.065)	(3.988)	(0.516)	(0.279)	(1.270)
Employed: PT far	2.213**	-0.509	0.660	1.382	0.0879	0.427	-0.601	0.267	-0.149	-0.311	0.706*	-1.445	0.103	0.00303	0.172
	(1.019)	(2.992)	(1.587)	(0.875)	(0.204)	(0.482)	(0.624)	(0.356)	(0.241)	(0.190)	(0.401)	(1.469)	(0.166)	(0.130)	(0.289)
Not Employed: senior	0.232	-5.524*	-1.343	-0.384	0.427*	-0.632	-1.115**	0.256	-0.557	-0.385***	-0.138	-6.472***	0.0720	-0.0329	0.172
	(1.476)	(2.832)	(1.499)	(0.764)	(0.234)	(0.906)	(0.444)	(0.472)	(0.414)	(0.146)	(0.338)	(1.898)	(0.118)	(0.0684)	(0.253)
Not Employed: under 65	2.309	-0.366	-1.604	0.0454	-0.0136	-0.0156	-0.389	-0.705*	-0.475	-0.241	0.214	-6.191***	-0.0886	0.0236	0.872*
	(1.545)	(3.249)	(1.719)	(0.832)	(0.180)	(0.575)	(0.685)	(0.425)	(0.363)	(0.169)	(0.450)	(1.910)	(0.0985)	(0.0999)	(0.515)
Observations	19,921	19,921	19,921	19,921	19,921	19,921	19,921	19,921	19,921	19,921	19,921	19,921	19,921	19,921	19,921
R-squared	0.171	0.405	0.398	0.163	0.314	0.141	0.392	0.192	0.276	0.0602	0.0795	0.446	0.261	0.547	0.232
Treated hh	329	329	329	329	329	329	329	329	329	329	329	329	329	329	329
Control hh	356	356	356	356	356	356	356	356	356	356	356	356	356	356	356
Mean dep var	21.47	93.36	39.34	10.82	2.115	5.889	5.601	1.864	2.487	1.372	3.800	18.99	1.010	1.098	7.544

Panel (b): Under time-of-day charge (kilometers/week)

VARIABLES	(1) Residential	(2) Grocery	(3) Other shop	(4) Park	(5) Sports	(6) Rural	(7) School	(8) Hospital	(9) Elderly	(10) Airport	(11) Petrol	(12) Commute	(13) Train	(14) For work	(15) Loop
Treatment = 15c peak 8c off-peak	0.167	-5.308	-6.861***	-2.778**	0.396	1.146	-0.342	-0.429	0.441	0.155	0.280	0.231	-0.220	0.228	0.709
	(1.691)	(4.210)	(2.559)	(1.155)	(0.336)	(0.790)	(0.877)	(0.752)	(0.467)	(0.311)	(0.658)	(2.176)	(0.326)	(0.591)	(0.580)
Treatment X Employed: PT far	1.672	14.16*	4.433	-0.584	-1.058*	-0.634	5.331***	0.663	0.666	0.721	0.507	-2.866	0.622	-0.965	0.0452
	(3.127)	(8.041)	(4.638)	(1.826)	(0.640)	(1.496)	(1.628)	(1.557)	(0.866)	(0.638)	(1.047)	(4.314)	(0.574)	(1.187)	(1.052)
Treatment X Not Employed: senior	-6.168**	5.156	-2.827	-3.737**	-0.193	-2.474	2.303**	-0.388	1.903**	0.937	-0.333	-0.271	-0.263	-1.346	0.423
	(2.886)	(8.529)	(4.953)	(1.451)	(0.782)	(1.606)	(1.133)	(1.161)	(0.892)	(0.585)	(1.256)	(3.159)	(0.284)	(1.158)	(1.025)
Treatment X Not Employed: under 65	0.407	5.624	2.715	0.253	0.200	-2.318	3.095**	0.294	-0.896	0.735	1.542	-0.618	-0.330	-1.357	4.564*
	(3.571)	(8.471)	(4.642)	(2.619)	(0.693)	(1.541)	(1.524)	(1.203)	(0.886)	(0.833)	(1.735)	(3.158)	(0.231)	(1.154)	(2.331)
Employed: PT far	1.951*	-1.079	0.465	1.587*	0.0387	0.323	-0.585	0.283	0.0723	-0.223	0.600	-1.705	0.0400	-0.0261	0.173
	(1.030)	(2.913)	(1.605)	(0.879)	(0.197)	(0.462)	(0.622)	(0.350)	(0.258)	(0.202)	(0.413)	(1.460)	(0.174)	(0.127)	(0.289)
Not Employed: senior	0.711	-5.295*	-1.362	-0.431	0.429*	-0.600	-1.079**	0.200	-0.382	-0.353**	0.0497	-6.422***	0.0705	-0.0512	0.180
	(1.454)	(2.769)	(1.465)	(0.735)	(0.234)	(0.857)	(0.448)	(0.460)	(0.339)	(0.152)	(0.359)	(1.906)	(0.107)	(0.0667)	(0.245)
Not Employed: under 65	2.034	-0.657	-1.501	0.406	-0.0485	-0.160	-0.343	-0.721*	-0.407	-0.217	0.0447	-6.158***	-0.0924	-0.00228	0.762
	(1.521)	(3.146)	(1.692)	(0.832)	(0.163)	(0.545)	(0.632)	(0.433)	(0.334)	(0.176)	(0.447)	(1.916)	(0.0992)	(0.0950)	(0.510)
Observations	20,278	20,278	20,278	20,278	20,278	20,278	20,278	20,278	20,278	20,278	20,278	20,278	20,278	20,278	20,278
R-squared	0.190	0.405	0.437	0.185	0.249	0.144	0.395	0.209	0.220	0.0851	0.149	0.484	0.623	0.551	0.237
Treated hh	344	344	344	344	344	344	344	344	344	344	344	344	344	344	344
Control hh	356	356	356	356	356	356	356	356	356	356	356	356	356	356	356
Mean dep var	22.13	93.04	42.55	11.53	1.850	5.112	5.458	2.139	2.623	1.631	4.006	18.89	1.449	1.046	7.478

Notes: Appendix C describes how trips were classified. All regressions also include (not shown) controls for baseline levels of the dependent variable and interactions between that baseline and treatment. The omitted category is employed drivers that live within 1 kilometer of public transport. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Summary statistics by income

	High income		Low income		High income employed		Low income employed	
	mean/sd	obs	diff/se	obs	mean/sd	obs	diff/se	obs
Household								
Age ≥ 65	0.100	622	0.38***	423	0.058	535	0.20***	209
	[0.30]		(0.025)		[0.23]		(0.025)	
Employed	0.86	630	-0.36***	429	1	542	0	213
	[0.35]		(0.026)		[0]		(0)	
Distance home SA1 to CBD (km)	22.1	630	5.05***	428	22.1	542	3.69***	213
	[15.0]		(1.00)		[15.0]		(1.23)	
Distance home SA1 to rail (km)	2.81	630	1.49***	428	2.82	542	0.69*	213
	[4.51]		(0.35)		[4.61]		(0.40)	
Vehicle								
Average litres fuel per 100km	8.56	627	0.46***	426	8.53	541	0.38**	212
	[2.16]		(0.14)		[2.17]		(0.18)	
Model year	2009.4	627	-2.72***	426	2009.4	541	-2.31***	212
	[4.39]		(0.32)		[4.32]		(0.38)	
Multiple Cars (=1)	0.61	630	-0.27***	429	0.62	542	-0.25***	213
	[0.49]		(0.030)		[0.49]		(0.039)	
Trip								
Distance traveled (km/day)	35.7	630	-6.81***	429	36.9	542	-2.75	213
	[23.0]		(1.35)		[23.8]		(1.87)	
Trips taken (/day)	3.48	630	-0.25**	429	3.48	542	0.066	213
	[1.66]		(0.10)		[1.68]		(0.14)	
Distance per trip (km/trip)	10.6	630	-1.38***	429	11.0	542	-0.82**	213
	[4.97]		(0.30)		[5.06]		(0.40)	
Time spent traveling (min/day)	54.9	630	-8.23***	429	56.4	542	-1.77	213
	[27.8]		(1.71)		[28.7]		(2.33)	
Share of time spent driving at peak (%)	36.6	630	-5.64***	429	37.3	542	-2.50**	213
	[15.1]		(0.90)		[15.6]		(1.24)	
Share of households ever commuting (%)	54.4	630	-28.6***	429	63.3	542	-11.2***	213
	[49.8]		(2.97)		[48.2]		(3.94)	
Average speed (km/hour)	34.6	630	-1.78***	429	35.1	542	-0.65	213
	[8.39]		(0.52)		[8.50]		(0.68)	
Share of hh-days entering CBD cordon (%)	5.21	630	-3.34***	429	5.65	542	-3.08***	213
	[10.7]		(0.56)		[11.4]		(0.83)	
Distance inside cordon (km/day)	0.39	630	-0.20***	429	0.42	542	-0.13**	213
	[0.73]		(0.042)		[0.77]		(0.061)	

Notes: Mean value for the High income group and differences in mean for the Low income group relative to the High income group. Standard deviations in square brackets, standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Changes in bill assuming no price responsiveness

	Households	Weekly	Change in weekly expenditures under		
		fuel tax	Distance charge	TOD charge	Cordon charge
	#	AUD	Δ AUD/%	Δ AUD/%	Δ AUD/%
Less than \$20,800	83	5.86	-4.06	-4.73	-3.26
			(75)	(77)	(77)
\$20,800 to \$41,600	162	7.19	-3.09	-3.76	-3.27
			(67)	(70)	(72)
\$41,600 to \$65,000	184	8.72	-0.056	-0.31	-0.83
			(60)	(60)	(64)
\$65,000 to \$104,000	260	8.90	1.59	1.69	1.39
			(52)	(52)	(54)
\$104,000 to \$156,000	203	9.36	2.39	2.79	2.21
			(49)	(49)	(48)
Greater than \$156,000	167	8.04	0.34	0.94	1.43
			(56)	(54)	(51)
Did not say	319	8.04	-0.54	-0.54	-0.48
			(59)	(59)	(61)

Notes: All above calculations based on baseline driving patterns. The average change in weekly bill is followed by, in parentheses, the percentage of the population in that income group that benefits from switching to that charge. For each road use charge the fuel tax is entirely replaced with the corresponding charge and annual vehicle registration fees are decreased by the amount needed to make the policy change revenue-neutral in the aggregate. That corresponds to a decrease, at the weekly level, of \$15.30 per vehicle for distance-based charges, \$14.84 per vehicle for TOD charges, and \$12.04 per vehicle for distance plus cordon charges. The analysis ignores secondary vehicles for multi-vehicle households.

Table 10: Characteristics of households losing more than $20/week under no demand response

			Loses under distance charge		Loses under TOD charge		Loses under cordon charge	
	mean/sd	obs	diff/se	obs	diff/se	obs	diff/se	obs
Household								
Annual Income	90,276	980	21,677**	47	24,821***	60	17,644*	43
			(8821.2)		(7843.3)		(9214.5)	
Age $\geq$ 65	0.28	1245	-0.13**	54	-0.21***	71	-0.18***	51
			(0.062)		(0.054)		(0.063)	
Employed	0.68	1270	0.19***	58	0.25***	77	0.24***	56
			(0.061)		(0.053)		(0.062)	
Distance home SA1 to CBD (km)	22.7	1271	12.8***	59	16.4***	78	4.41**	57
			(2.06)		(1.78)		(2.12)	
Distance home SA1 to rail (km)	3.15	1271	2.74***	59	3.53***	78	1.07	57
			(0.74)		(0.65)		(0.76)	
Vehicle								
Average litres fuel per 100km	8.81	1273	-0.75**	49	-0.51*	68	-1.34***	47
			(0.34)		(0.29)		(0.34)	
Model year	2008.2	1273	3.08***	49	2.40***	68	2.95***	47
			(0.75)		(0.64)		(0.77)	
Multiple Cars (=1)	0.49	1269	0.15**	55	0.15**	74	0.14**	53
			(0.069)		(0.060)		(0.070)	
Trip								
Distance traveled (km/day)	29.1	1273	54.5***	60	49.6***	79	41.4***	58
			(2.43)		(2.10)		(2.66)	
Trips taken (/day)	3.25	1273	1.67***	60	1.56***	79	1.22***	58
			(0.21)		(0.19)		(0.22)	
Distance per trip (km/trip)	9.48	1273	7.69***	60	7.32***	79	6.39***	58
			(0.61)		(0.53)		(0.63)	
Share of time spent driving at peak (%)	33.9	1273	-2.85	60	6.99***	79	1.79	58
			(1.94)		(1.69)		(1.97)	
Share of households ever commuting (%)	40.1	1273	3.35	60	25.5***	79	17.6***	58
			(6.51)		(5.68)		(6.61)	
Share of hh-days entering CBD cordon (%)	2.92	1273	2.93**	60	4.48***	79	21.6***	58
			(1.21)		(1.06)		(1.09)	
Distance inside cordon (km/day)	0.25	1273	0.36***	60	0.29***	79	1.27***	58
			(0.086)		(0.076)		(0.081)	
Fraction km on Top 25 congested roads	0.10	1273	0.0050	60	0.0023	79	0.046***	58
			(0.011)		(0.010)		(0.012)	

Notes: All above calculations based on baseline driving patterns. For each road use charge the fuel tax is entirely replaced with the corresponding charge and annual vehicle registration fees are decreased by the amount needed to make the policy change revenue-neutral in the aggregate. That corresponds to a decrease, at the weekly level, of $15.30 per vehicle for distance-based charges, $14.84 per vehicle for TOD charges, and $12.04 per vehicle for distance plus cordon charges. The analysis ignores secondary vehicles for multi-vehicle households.

Table 11: Changes in consumer surplus

Panel (a) Distance-based charge

Annual Income	Households	Elasticity	% Δ CS		Elasticity	% Δ CS	
			(1)	(2)		(1)	(2)
Less than $20,800	83	-0.121	-12.35	2.68	-0.567	-10.38	3.75
$20,800 to $41,600	162	-0.121	-13.58	1.99	-0.146	-13.45	2.11
$41,600 to $65,000	184	-0.121	-16.16	-0.10	-0.145	-16.01	0.03
$65,000 to $104,000	260	-0.121	-17.26	-1.21	0.070	-18.66	-1.85
$104,000 to $156,000	203	-0.121	-18.04	-1.85	-0.229	-17.27	-1.39
Greater than $156,000	167	-0.121	-16.22	-0.48	0.066	-17.50	-1.05
Did not say	323	-0.121	-15.60	0.18	-0.209	-15.06	0.51

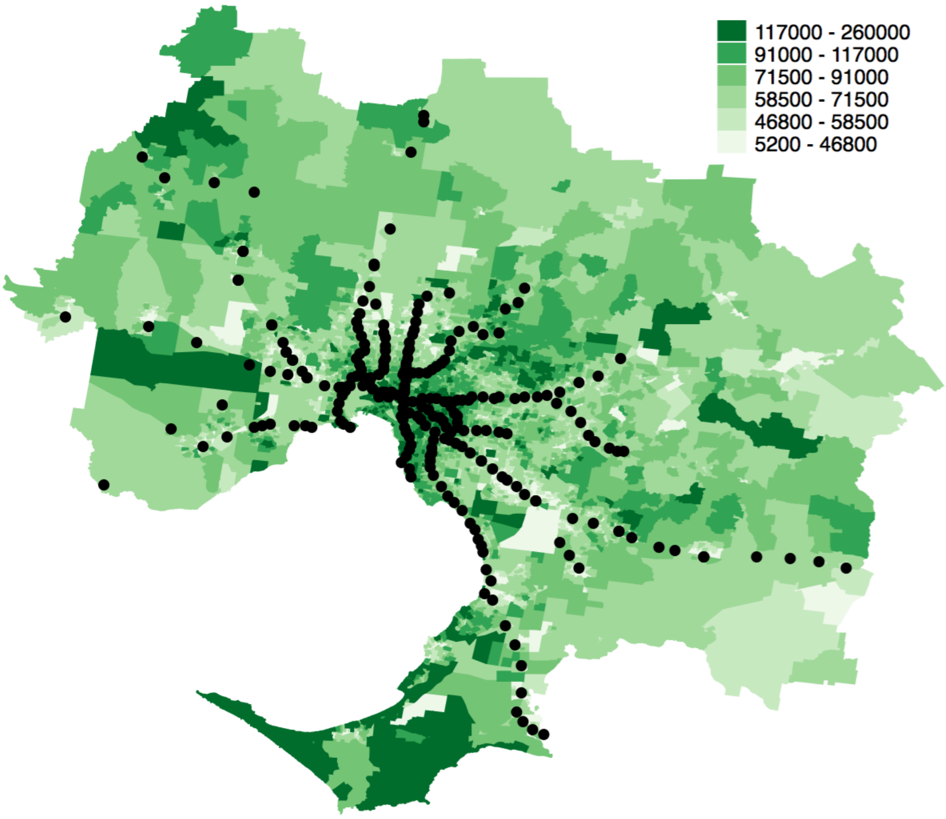
Panel (b) Time-of-day charge

Annual Income	Households	Elasticity		% Δ CS		Elasticity		% Δ CS	
		peak	off-peak	(1)	(2)	peak	off-peak	(1)	(2)
Less than $20,800	83	-0.106	0.008	-12.57	3.56	-0.299	-0.349	-11.23	4.31
$20,800 to $41,600	162	-0.106	0.008	-13.82	2.84	-0.283	0.008	-13.34	3.25
$41,600 to $65,000	184	-0.106	0.008	-16.75	0.41	-0.306	-0.058	-15.82	1.05
$65,000 to $104,000	260	-0.106	0.008	-18.11	-0.97	-0.051	0.136	-18.81	-1.21
$104,000 to $156,000	203	-0.106	0.008	-19.08	-1.79	-0.072	-0.173	-18.63	-1.56
Greater than $156,000	167	-0.106	0.008	-17.35	-0.53	0.016	0.400	-19.23	-1.31
Did not say	323	-0.106	0.008	-16.33	0.54	-0.029	-0.063	-16.43	0.52

Notes: Column (1) shows percentage change in consumer surplus from road use charges. Column (2) shows change in consumer surplus from road use charge assuming revenue-recycling. Under revenue-recycling the fuel tax is entirely replaced and annual vehicle registration fees are decreased by the amount needed to make the policy change revenue-neutral in the aggregate. The change in weekly registration fee corresponds to $1.95 and $1.97 per vehicle for distance-based charges for constant elasticity and elasticity that varies by income group, respectively, and $1.93 and $1.94 per vehicle for time-of-day charges with constant elasticity and elasticity that varies by income group, respectively. The redistribution calculations take into account the impact of higher per kilometer prices on kilometers driven. The analysis ignores secondary vehicles for multi-vehicle households.

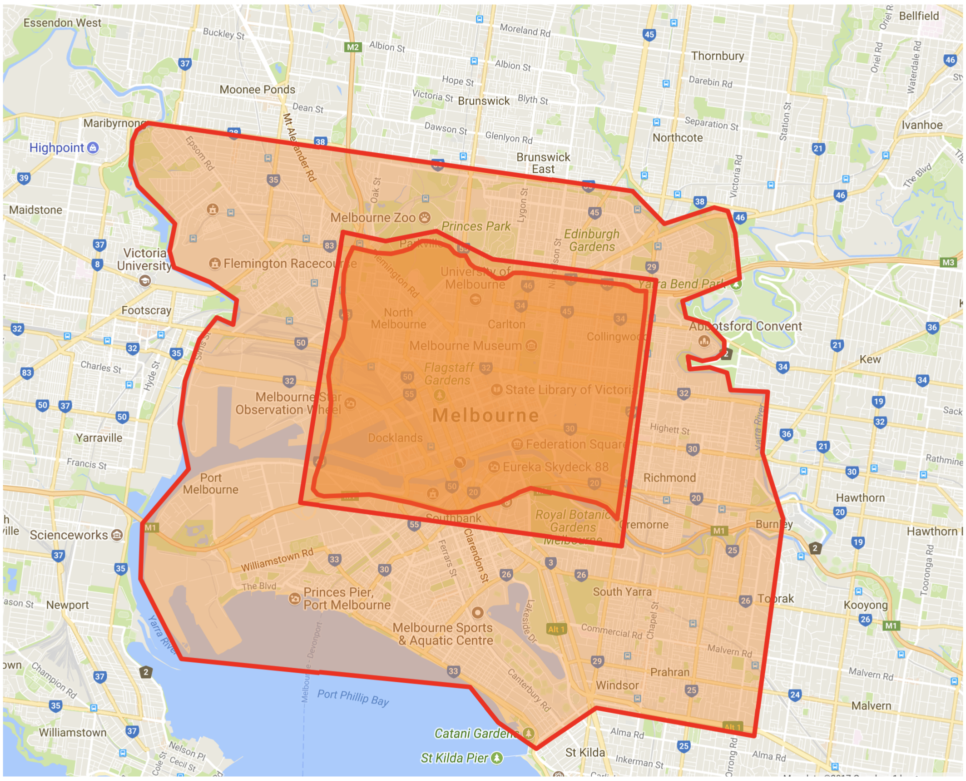
B Figures

Figure 1: Variation in income and access to public transport



Notes: Map of Greater Metropolitan Melbourne. Green shading represents median income at the SA1 level from the 2011 Australian Census. Black dots represent commuter rail train stations. There is also a network of trams in and around the city center that we use in our analysis.

Figure 2: Cordon area



Notes: The cordon charge applied to any day in which a driver entered the inner cordon (dark shade) at a priced time. This region is bounded by Alexandra Parade and Elliott Avenue to the North, CityLink to the West and South, and Hoddle Street to the East. Note that travel along these boundary roads does not incur a cordon charge. We also investigate road use in two additional regions: the boundary area around the inner cordon, depicted above, and an outer cordon, also depicted above, that was discussed as a potential candidate for a cordon charge by Infrastructure Victoria (2016). The inner cordon is approximately 5 kilometers wide. At its widest, the outer cordon is 10 kilometers wide.

Figure 3: Per kilometer cost of driving with and without distance-based charge

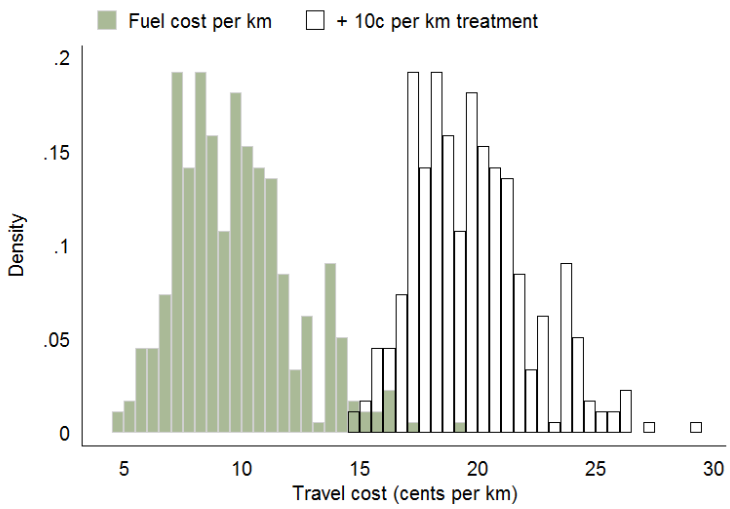
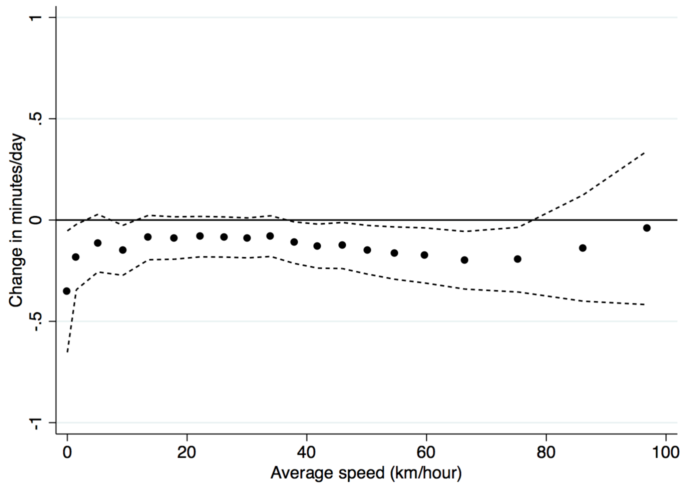
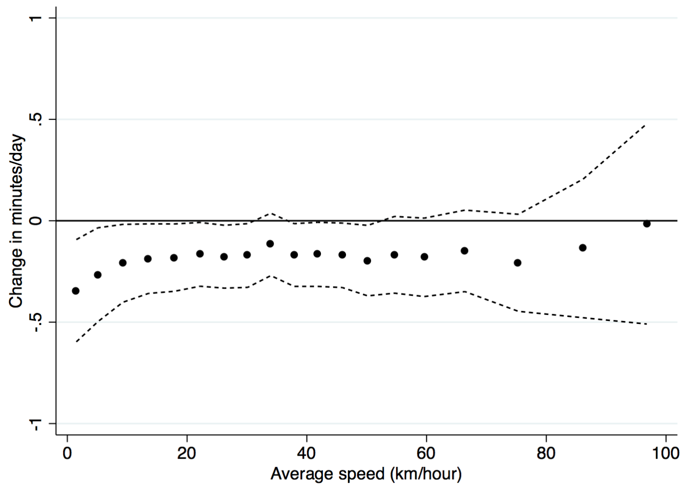


Figure 4: Effect of road use charge on time spent traveling at different speeds

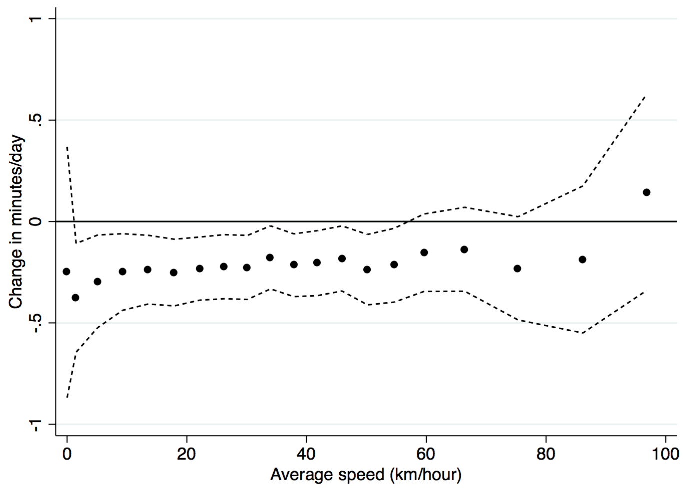
Panel (a) Uniform VMT charge



Panel (b) Time-of-day VMT charge

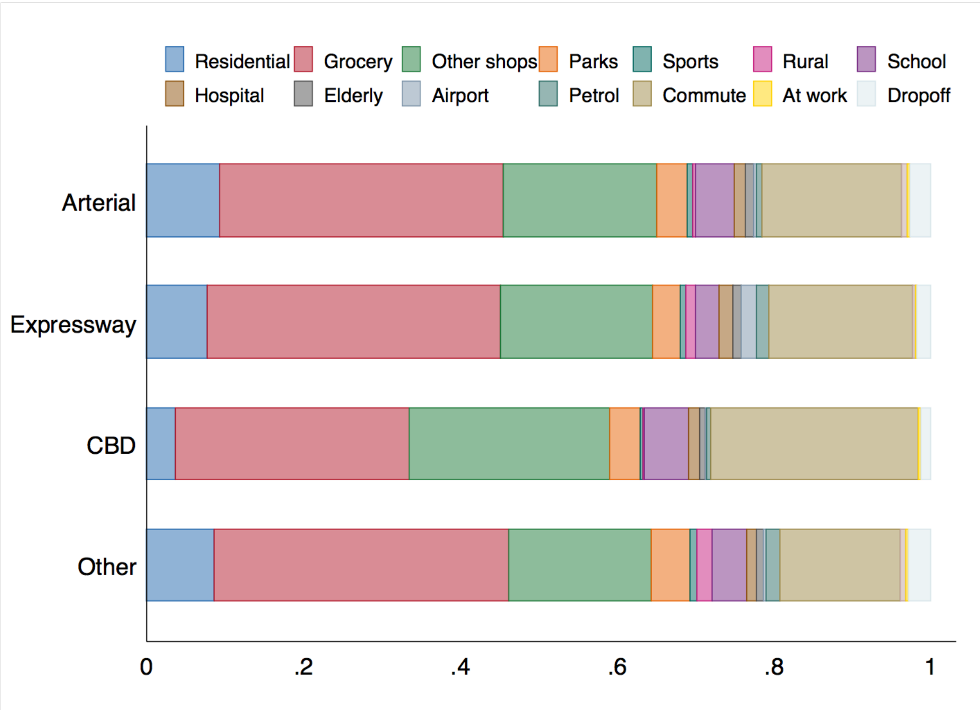


Panel (c) Uniform VMT and cordon charge



Notes: The dependent variable is minutes per day spent driving at the given speed. Zero-speed readings are only included if they occur mid-trip. Panel (a) represents the effect the per kilometer charge of 10c per kilometer. Panel (b) represents the effect of the time-of-day charge of 15c per kilometer peak, 8c per kilometer off-peak. Peak is 7-9am and 3-6pm Monday-Friday. Panel (c) represents the effect of the uniform VMT of 8c per kilometer plus $8 per day for cordon entry. Black dashed lines are 95% confidence intervals.

Figure 5: Baseline driving by road type and destination at peak times



Notes: This figure shows the allocation of peak-time kilometers traveled on each type of roads to the destinations involved. "Expressway" and "Arterial" refer to the four expressways and 21 arterials in the Top 25 most congested roads. "CBD" refers to driving within the inner city cordon. "Other" represents trips on all other roads in the network.

Figure 6: Daily treatment effects by destination

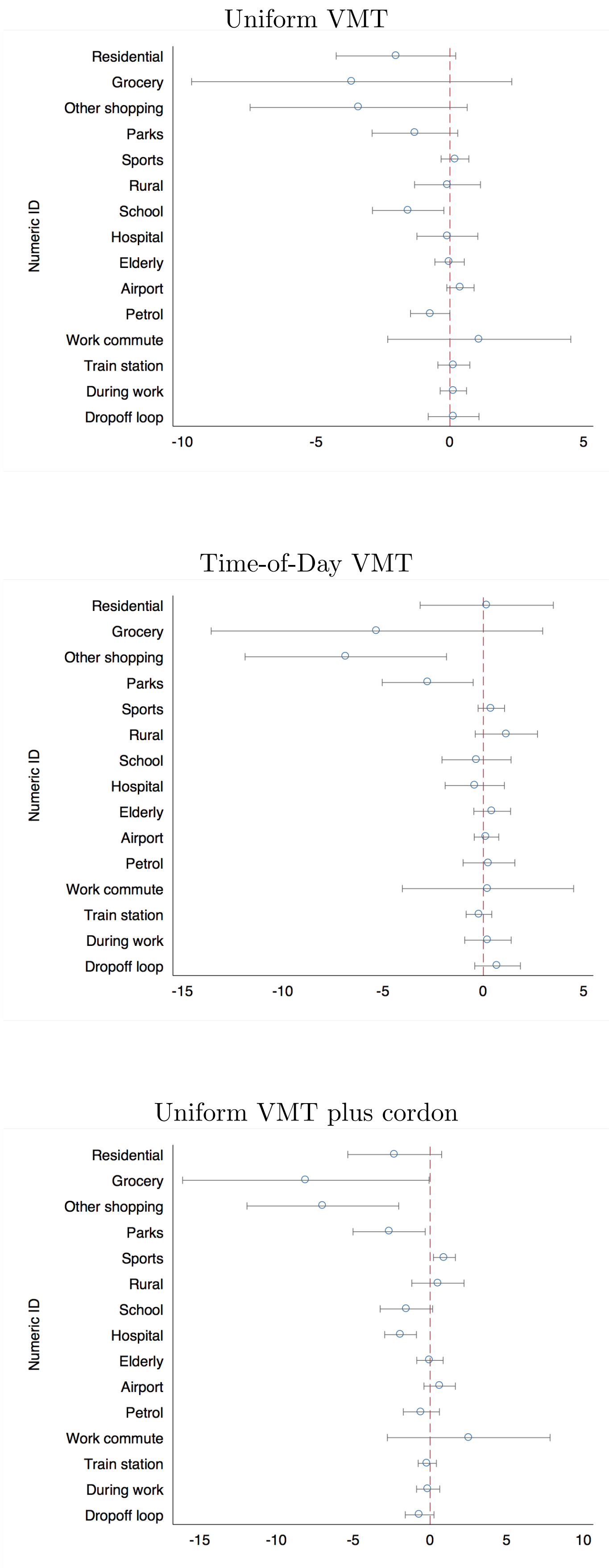


Figure 7: Distribution of Δ travel expenditures under uniform VMT charge

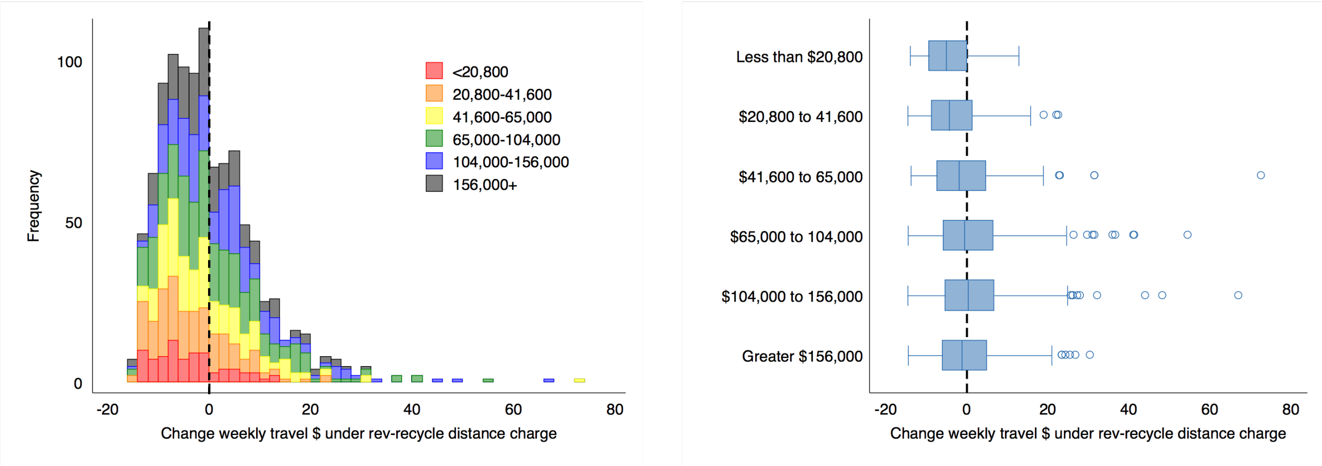


Figure 8: Δ travel expenditures by income and distance from public transport, no demand response

Uniform VMT

	Distance to public transit			
Income	0 to 500m	500m - 1km	1 - 2.5km	More 2.5 km
Less than $20,800	-6.66	-5.01	-3.31	-1.10
$20,800 to 41,600	-6.20	-4.03	-2.10	-1.77
$41,600 to 65,000	-4.59	-1.10	2.01	1.66
$65,000 to 104,000	-2.51	0.97	2.11	4.90
$104,000 to 156,000	0.80	-1.33	2.29	7.75
Greater $156,000	-1.79	0.40	-0.21	5.89

Time-of-Day VMT

	Distance to public transit			
Income	0 to 500m	500m - 1km	1 - 2.5km	More 2.5 km
Less than $20,800	-7.85	-6.28	-3.56	-1.23
$20,800 to 41,600	-7.14	-4.59	-2.75	-2.45
$41,600 to 65,000	-4.90	-1.25	1.82	1.34
$65,000 to 104,000	-2.78	0.91	2.15	5.53
$104,000 to 156,000	0.90	-1.67	2.79	8.95
Greater $156,000	-1.81	0.76	0.95	7.55

Uniform VMT plus cordon

	Distance to public transit			
Income	0 to 500m	500m - 1km	1 - 2.5km	More 2.5 km
Less than $20,800	-3.80	-4.73	-2.46	-1.82
$20,800 to 41,600	-4.06	-3.81	-2.82	-2.66
$41,600 to 65,000	-3.09	-1.86	0.41	0.19
$65,000 to 104,000	-1.04	1.68	2.16	2.15
$104,000 to 156,000	2.21	-0.70	1.80	5.50
Greater $156,000	0.82	1.92	0.75	3.00

For Online Publication

C Classifying destinations

C.1 Data sources

We use a range of sources to identity trip destinations. This includes spatial Vicmap and PTV data available freely from the Victorian governments data repository at `https://www.data.vic.gov.au/`. We source polygon and point of interest shape files including:

- Planning scheme overlay - Vicmap Planning. We use this to identify the planning zone for all trip destinations within Victoria. This dataset contains polygon features representing overlay controls for all Victorian planning schemes. The State of Victoria, Department of Environment, Land, Water & Planning 2018
- Vicmap Features of Interest (FoI). This dataset series contains a range of features of interest represented by points, lines and/or polygons within Victoria. The State of Victoria, Department of Environment, Land, Water & Planning 2018
- Public Transport a collection of PTV datasets. PTV Bus Route Metro PTV Bus Route Regional PTV Bus Stop PTV Train Carpark PTV Train Corridor Centreline PTV Train Station PTV Train Station Bike Storage PTV Train Station Platform PTV Train Track Centreline PTV Tram Route PTV Tram Stop PTV Tram Track Centreline Excludes the restricted school bus routes. The State of Victoria, Public Transport Victoria 2018
- Schools locations from the Victorian Department of Education and Training `https://www.data.vic.gov.au/data/dataset/school-locations-2017`

For each individual trip, we have also used the Google Places api to collect information on all points of interest within 50 meters of the stop coordinates.

C.2 Work commutes and during work trips

Identifying workplaces and typical work days/hours

We first identify workplaces and work hours using an algorithm that looks for repeated visits to the same location for 5-15 hrs, but not overnight. We begin by identifying the 50 most travelled (non-home) destinations by households by looking at all trips that end within a 500-meter radius. To do this, we round the GPS coordinates to the nearest 100 meters, calculate the centroid of those destinations and then merge all destinations within 500 meters of that destination. Each trip within the full data set is then identified as to whether it belongs to to one of the unique popular destinations by household (destination number 1 is the most frequently visited up to a maximum possible destination 50)

Using the full trip data set with popular destinations flagged we then look only at trips to popular destination with at least 10 visits within the study period. We start by dropping all trips with a stop duration (time spent parked at the destination) of less than 2hrs. These short stops/drop-offs are unhelpful for identifying work places and work hours.

For each household - popular destination - date combination we then check if the car is parked overnight at that location for more than 9 hrs. We then flag any destination where the car is parked overnight more than 30% of the time and eliminate it from it from the possible data set of workplaces. This allows for people who work 8 hr overnight shifts but drops destinations which are likely to be residential.

Looking at the subsample of possible work trips we then check to see if at least 50% of the remaining trips to that destination are greater than 4hrs. 4 hours is chosen as the lower bound for part time work in this case.

We then drop all observations outside of 5 to 15 hours and trips parked overnight. Within each day we further refine the sample by looking only at trips to the place parked for the longest time at a popular destination, on each date. This helps to exclude long after work visits to residential addresses.

We also require that household typically stop at the destination around the same time of day. To do this we calculate the 20th and 80th percentile trip stop time at each destination and check it is within a three-hour window. Alternatively, we also keep any destination with a 50th percentile stop duration of at least 8hrs, to account for shift workers with irregular hours during the week.

After this process is complete we then again drop all destinations with less than 10 valid visits remaining.

Finally to identify work days and work hours we then turn to the pattern of trips across the week and require two things. (1) At least 10% of observations are on an individual day of the week for it to be counted as a "workday". This allows for some long trips outside of work hours (e.g. if you shop at the shopping mall you work at). (2) At least 2 and up to 6 days per week are flagged as workdays. Places only visited one day per week are less likely to be work and more likely to be social (i.e. golf course). Places visited regularly every day of the week are more likely to be residential places not yet dropped.

Identifying trips to work for work purposes

We then begin by identifying all trips to a work location on a workday, during work hours. These trips can be of any length less than 15hrs. However, we require that the driver is away from their home destination for least 4 hours. We add to this any other trips to a workplace of 5-15hrs that take place outside of work hours.

Identifying workplace commutes and trips during work

To identify all stops on the way to/from work as workplace commutes and stops during the day while at work as during work, we use the following algorithm. We begin by uniquely identifying all home-to-home circuits on a day as "tripblocks." While most identified work trips take place from home, we also need to account for overnight stops at alternative residential addresses, without breaking up tripblocks that are people working the night shift. To do this we split all trip blocks where: the date changes from start to finish; and you don't stop at work; and you stop for at least 6hrs.

After identifying tripsblocks that contain valid trips to work, we work out the time of day that you first arrive at work and the time of day you last leave work. Finally, we allocate all trips in a work tripblock that occur before you first arrive at work and after you last leave work as workplace commutes. This is regardless of where you go, as long as you have not yet reached work or returned to your home/overnight residence. We do however put a 3hr time limit on trips, requiring that trips must be no more than 3hrs before you arrive at work and no more than 3hrs after you last leave work for the day. All trips between arriving at work and leaving work are classed as During work trips. Correcting for commutes to train stations

All work commute trips that have a train station as the work location as listed as train station trips rather than workplace commutes.

C.3 Identifying other destinations

For each trip, we flag whether that trip is possibly from one of 11 destination types. An individual trip may flag as possibly being more than one type of trip and so we use an order of precedence for the flags. This is explained further later.

We begin by aggregating each of the possible planning zone's (from Vicmap Planning) into the one of the following categories. 1: Residential, 2: Commercial, 3: Industrial, 4: Green wedge, 5: Urban growth, 6: Rural, 7: Mixed use.

Retail/services

To classify as a shopping trip, the stop duration has to be no greater than five hours. In addition, we identify shopping trips using a combination of zone classifications, Google place results, and time of day using the following rules: Public use - local government (PUZ6) is typically local government-provided

Zone	Google places within 50m of	Time of day
Commercial	—	any
Residential	any shop	6am-10pm
Industrial	any shop	6am-10pm
Green wedge	any shop	6am-10pm
Urban growth	any shop	6am-10pm
Mixed use	any shop	6am-10pm
Public use - local government	any shop	6am-10pm
Public park and recreation	at least 2 shops	6am-10pm
–	at least 3 shops	6am-10pm

parking or shopping centres. We flag the stops near public park and recreation zones with multiple adjacent shops to represent the likelihood that the driver is visiting the shops near the park, not the park itself.

Residential

We flag destinations as residential if the destination:

- Residential zone: parked >20 meters from shops, any time of day
- Urban growth zone: parked >50 meters from shops, any time of day
- Mixed use zone: trip not in a FoI or near a PoI, and not already flagged as Retail/services

We also flag whether the residential destination is a frequent destination or an occasional one.

Petrol stations

For stops that are less than 10 minutes long, we flag the destination as a petrol station if Google places returns a petrol station within 20 meters. For stops that are more than 10 minutes long, we only flag the destination as a petrol station if the closest Google place result is a petrol station.

Melbourne and Avalon airports

For Melbourne airport, all trips in short term parking (defined as within 500 metres of airport drop off zone Terminal 2 - coordinates -37.670100, 144.849353), less than 24hrs. Also, all trips parked more than 12hrs within 5km of airport and within the airport planning zone. This captures long term airport and private parking options but excludes airport workers.

For Avalon airport, all parking within 300 meters of terminal (coordinates -38.026316, 144.472956) within the airports planning zone (SUZ11).

Parks and outdoor sports

A destination is classified as park/outdoors if it lies within a Public conservation and resource zone (PCRZ). This zone is almost exclusively national and state park, and includes beaches. We also classify a destination as a park if it lies within a Public park and recreation zone (PPRZ) and has fewer than two shops within 50 meters. We also classify the destination as a park if it is located in any of the following features of interest: "park", "golf course", "conservation park", "gardens", "national park", "sports ground", "tennis court", "sports complex", and "caravan park".

Rural

All rural zone destinations flagged as rural. In addition, we flag all Greenwedge destinations as rural if parked >50 meters from shops, any time of day.

Hospitals and aged care

Hospital is flagged if car is parked in a feature of interest polygon label "hospital complex". Aged care is flagged for visits of less than 5hrs to "retirement village" FoI polygons and within 50 meters of "aged care" PoI's.

Schools and childcare

We classify school trips using two sources: the locations of all kinder, primary, and secondary schools from the Victorian Department of Education and Training, and PoI type "care facility" and subtype "child care" for day care. School trips can be particularly tricky to identify because many young children walk or bicycle to primary school and many older children take public transport or school buses to secondary school.

To be conservative, we restrict all potential school trips to days when school is in session (dropping all weekends and school holidays) and to households that have identified that they have children. There are also trips in the data that clearly appear to be school pick-ups by grandparents, and drop-offs at school buildings on holidays, but allowing for those trips greatly increases the potential for false positives.

We then create a set of possible school trips. We restrict drop-offs to arrivals before 9am and pick-ups to arrivals between 2:30pm and 7pm. Because many schools have playing fields, and PoI tend to be centred on the middle of the property and not by the front door, we consider all pick-ups and drop-offs within 200 meters of a school.

We then identify for each household a set of schools, based on frequency of eligible trips, with a minimum of 10 visits, and at most one school per child in the household. We flag all visits to and from those schools at eligible times as school trips. We check and confirm that school trips are much more likely on days with rain.

C.4 Allocating trips to destinations

We first flag all trips that stop at home as "home" trips. We use the following order of precedence for allocating trips where a trip has more than one flag. Lowest rank to highest rank: (1) Residential, (2) Rural, (3) Shopping, (4) Parks, (5) Schools, (6) Hospitals, (7) Aged care, (8) Airport, (9) Petrol station, (10) Work commute, (11) Train station, (12) During work.

At this stage 97% of trips are allocated. For the remaining trips we take the following approach. First we look at any remaining allocated trips within a FoI. These trips are allocated directly to their trip type based on the type of FoI. For the remaining unallocated trips we then consider any point of interest (PoI) within 20 meters of, or closest to the trip destination and again allocate directly to trip types based on the type of PoI.

In the following order, we allocate the small fraction of trips remaining unallocated as:

1. Residential if there is at least one shop nearby and you stop more than 12hrs
2. Retail/services if there is at least one shop nearby and you stop less than 12hrs
3. Schools if you are within 50 meters of an education facility.
4. Petrol station if close to a petrol station
5. Retail/services if there is at least one shop nearby
6. Retail/services if you stop anywhere less than 5hrs
7. Residential if you stop more than 5hrs

For trips that end at home we allocate them to the category where the trip started rather than ended. For example, if you drive from to the local supermarket and then back to home, both trips would count as shopping trips.

Finally, we define trips that stop and start at home as drop-off loops. We are able to classify a subset of these as potential school or train drop-offs.

C.5 Other variables

Employment Status

In our analysis, we parse many of our results by employment status. As part of the experiment, the primary driver of the vehicle used in the study was asked for their employment status at the start of the experiment. We assume that if the primary driver was employed in any capacity at the start of the study, then that household is an "employed" household. For the remaining households, we classify them as employed, if they have a clearly identified workplace. All other households are classed as not employed. All other households are defined as not employed.

We assume that households employed, but with identified work location, work in the CBD.

Senior Status

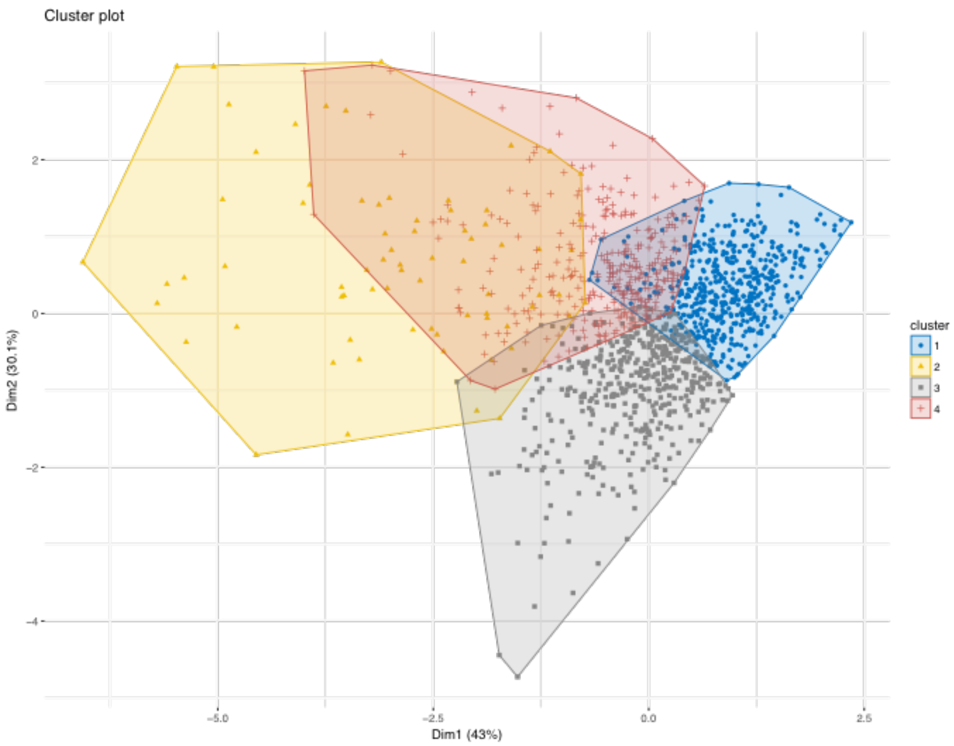
All household 65 years and older are classified as senior, unless classified as employed.

D Clustering households based on driving patterns

Data are normalized to have mean zero and variance one. Missing values are imputed using R's *mice* function.

To find the optimal number of clusters, we create clusters for 1:n (specified by user) clusters, calculate a test statistic for each, and then plot that statistic as a function of the number clusters. We look for an 'elbow' in the plot, the point at which adding another cluster does not change the criterion very much. The tradeoff is between explaining the data well, and grouping individuals well. (In the extreme we can always explain the data perfectly if each individual is allocated to their own cluster.)

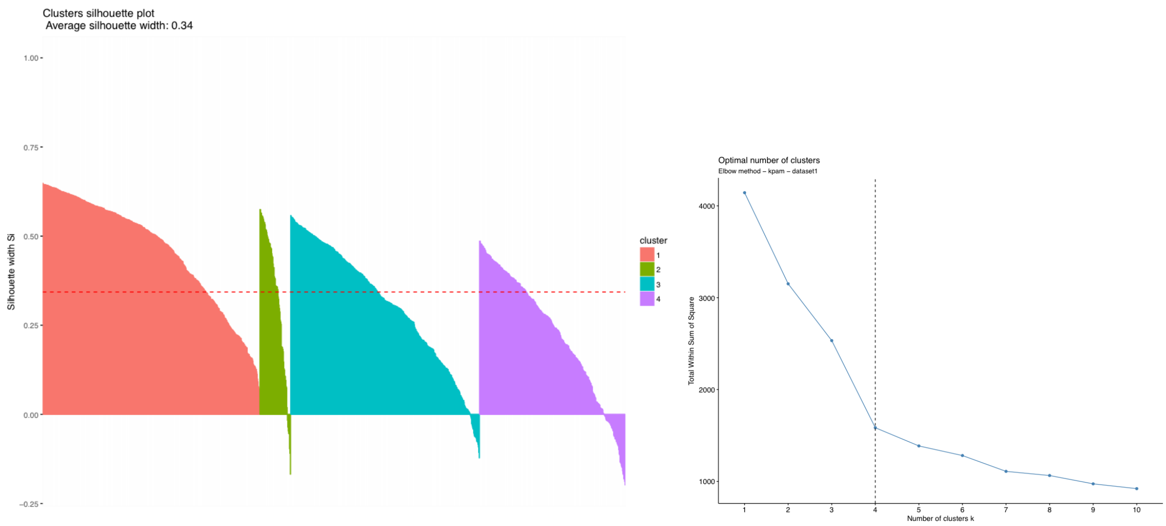
Figure D.1: Visualising clusters in two compressed dimensions



The two most common algorithms are: k-means and k-medoids, where each observation is put into the cluster with the nearest mean (centroid, k-means) or nearest medoid (k-medoids). The K-mediod algorithm minimises the sum of pairwise dissimilarities instead of Euclidiean distances. We opt for K-medoids as they tend to be more robust to outliers and noise. The three criteria used are: cluster sum of squares (WSS), silhouette (closeness of observations to their own cluster vs. others), and the gap statistic (the change in within-cluster dispersion relative to that expected under a reference null distribution). (Tibshirani, Walther and Hastie, 2001)

We then compute the clusters based on only three outcome variables, all calculated based on baseline

Figure D.2: Overlap across clusters, optimal number of clusters



driving: distance traveled (km/day), share of time spent driving at peak times (%), and share of hh-days entering the CBD cordon (%). A summary of means by cluster groups is shown in Table D.1. The results of the cluster analysis are remarkably similar to the disaggregation used in the literature. The first cluster contains many seniors. The second cluster contains wealthy inner-suburb households. The third cluster is almost exclusively made up of families with children. The fourth cluster contains primarily outer-suburb households.

We can also visualise the results across two aggregated dimensions which aim to show as much variation in the data as possible across two axes (using the fviz_cluster function in R) in Figure D.1. As can be seen, there is some good separation between clusters, but also some overlap too, suggesting the data is decently but not perfectly well suited to clustering.

A visual evaluation of the cluster process is the silhouette method, which shows, on a scale of -1 to 1, how close an observation is to other members of its cluster versus other clusters. Close to 1 is good; values below 0 indicate individuals potentially allocated to the wrong cluster. We present the results of the silhouette analysis in Figure D.2. We note that cluster 1 is well-defined. Cluster 2, 3 and 4 are largely well-defined but have some values below 0, indicating potential mis-allocation.

Table D.1: k-medoids clusters of households in experiment based on driving patterns

Cluster	**1**	**2**	**3**	**4**
Driving during baseline				
Distance traveled (km/day)	19.62	45.31	26.95	58.80
Share of time spent driving at peak (%)	22.36	42.71	47.9	32.58
Share of hh-days entering CBD cordon (%)	1.62	37.93	1.49	2.75
Trips taken (/day)	2.49	3.69	3.39	4.64
Time spent traveling (min/day)	35.51	73.32	46.02	79.21
Time traveling at peak (min/day)	8	31.07	22.21	25.95
Share of time spent commuting (%)	4.46	**37.26**	20.76	14.02
Average trip duration (min/trip)	15.86	20.33	14.60	17.97
Average duration of commutes (min/day)	48.23	78.87	55.18	63.87
Distance per trip (km/trip)	8.73	12.45	8.69	13.64
Average speed (km/hour)	30.70	32.40	32.31	40.48
Distance per trip (km/trip)	8.73	12.45	8.69	13.64
Distance inside cordon (km/day)	0.18	2.14	0.13	0.29
Distance cordon border (km/day)	0.28	1.95	0.29	0.72
Distance outer cordon (km/day)	0.72	3.64	0.66	1.17
Primary driver characteristics				
Female	0.49	0.47	0.57	0.46
Age $\geq$ 65	**0.41**	0.10	0.20	0.19
Employed	0.53	0.95	0.80	0.77
Household characteristics				
Income	79,381	**130,858**	98,477	92,935
Has children	0.44	0.59	**0.91**	0.79
Distance home SA1 to CBD (km)	21.49	**14.77**	22.72	**29.76**
Distance home SA1 to rail (km)	3.14	1.74	2.81	4.66
Distance home SA1 to rail/tram (km)	2.99	1.45	2.68	**4.58**
Vehicle characteristics				
More than one vehicle	0.42	0.56	0.53	0.6
Average litres fuel per 100km	8.76	8.20	8.73	8.89
Model year	2007	2010	2009	2009
Petrol (=1)	0.85	0.79	0.86	0.78
Visible GPS (=1)	0.41	0.16	0.20	0.15

Notes: Results of clustering based on Distance traveled (km/day), Share of time spent driving at peak (%), and Share of hh-days entering CBD cordon (%). Mean values shown. The first cluster contains many seniors. The second cluster contains wealthy inner-suburb households. The third cluster is almost exclusively made up of families with children. The fourth cluster contains primarily outer-suburb households.

Table D.2: Weekly treatment effects by destination and driver-type

Panel (a): Under cordon charge (kilometers/week

VARIABLES	(1) Residential	(2) Grocery	(3) Other shop	(4) Park	(5) Sports	(6) Rural	(7) School	(8) Hospital	(9) Elderly	(10) Airport	(11) Petrol	(12) Commute	(13) Train	(14) For work	(15) Loop
Treatment = 8c per km and cordon	-2.232	-7.727*	-6.813***	-2.710**	0.956***	0.500	-1.493*	-1.928***	-0.00407	0.656	-0.512	3.324	-0.147	-0.136	-0.655
	(1.572)	(4.105)	(2.521)	(1.195)	(0.364)	(0.878)	(0.856)	(0.532)	(0.445)	(0.523)	(0.593)	(2.763)	(0.307)	(0.391)	(0.480)
Treatment X Cluster 2	-4.704	13.59	-2.974	-3.237	0.516	0.826	0.419	-0.317	0.258	1.648	0.488	13.35	3.572	2.046	-0.650
	(4.917)	(16.00)	(11.18)	(3.114)	(0.746)	(2.794)	(2.611)	(0.662)	(1.069)	(1.851)	(1.375)	(18.24)	(2.659)	(1.679)	(0.840)
Treatment X Cluster 3	-2.439	-0.180	1.152	-0.395	0.923*	1.564	-0.630	0.267	-0.593	-0.334	-1.089	1.061	0.232	-0.191	-0.126
	(2.142)	(5.897)	(3.237)	(1.630)	(0.485)	(1.498)	(1.487)	(0.462)	(0.738)	(0.516)	(0.809)	(5.185)	(0.252)	(0.257)	(0.739)
Treatment X Cluster 4	-0.405	2.178	1.624	-1.523	1.696*	2.973*	2.001	0.771	-0.276	0.750	-0.281	4.055	0.129	0.188	0.203
	(3.550)	(9.464)	(6.426)	(2.201)	(0.989)	(1.718)	(2.020)	(0.833)	(0.840)	(0.712)	(1.269)	(5.059)	(0.525)	(0.677)	(0.796)
Cluster 2	0.496	-5.398	-1.289	-1.464	-0.900	-0.981	-0.679	-0.345	-0.00992	0.0803	-0.218	8.112	-0.302**	-1.786	-0.654
	(1.513)	(4.694)	(3.650)	(1.445)	(0.615)	(1.046)	(0.922)	(0.347)	(0.317)	(0.301)	(0.454)	(5.071)	(0.151)	(1.345)	(0.587)
Cluster 3	1.076	1.484	1.250	0.412	-0.185	0.220	0.769	-0.205	0.339	0.111	0.615***	3.880**	-0.126	0.0670	0.583**
	(0.835)	(2.245)	(1.184)	(0.701)	(0.171)	(0.423)	(0.633)	(0.325)	(0.229)	(0.165)	(0.235)	(1.834)	(0.128)	(0.0745)	(0.274)
Cluster 4	3.515**	-2.619	3.906**	1.757*	0.257	-0.627	-0.0536	0.328	0.258	0.0655	1.599***	3.199*	0.175	0.377	-0.181
	(1.625)	(4.843)	(1.908)	(1.042)	(0.217)	(0.492)	(0.460)	(0.422)	(0.284)	(0.154)	(0.456)	(1.692)	(0.184)	(0.265)	(0.341)
Observations	19,921	19,921	19,921	19,921	19,921	19,921	19,921	19,921	19,921	19,921	19,921	19,921	19,921	19,921	19,921
R-squared	0.171	0.405	0.399	0.163	0.315	0.141	0.392	0.192	0.276	0.0602	0.0801	0.444	0.262	0.548	0.232
Treated hh	329	329	329	329	329	329	329	329	329	329	329	329	329	329	329
Control hh	356	356	356	356	356	356	356	356	356	356	356	356	356	356	356
Mean dep var	21.47	93.36	39.34	10.82	2.115	5.889	5.601	1.864	2.487	1.372	3.800	18.99	1.010	1.098	7.544

Panel (b): Under time-of-day charge (kilometers/week)

VARIABLES	(1) Residential	(2) Grocery	(3) Other shop	(4) Park	(5) Sports	(6) Rural	(7) School	(8) Hospital	(9) Elderly	(10) Airport	(11) Petrol	(12) Commute	(13) Train	(14) For work	(15) Loop
Treatment = 15c peak 8c off-peak	0.215	-5.358	-6.885***	-2.724**	0.390	1.152	-0.333	-0.460	0.408	0.156	0.287	0.404	-0.223	0.239	0.737
	(1.703)	(4.203)	(2.554)	(1.153)	(0.332)	(0.795)	(0.887)	(0.740)	(0.465)	(0.312)	(0.651)	(2.174)	(0.324)	(0.585)	(0.584)
Treatment X Cluster 2	-4.930	9.452	11.88	-0.0549	2.589	1.651	-1.106	1.803	0.453	-0.497	-0.229	-30.57***	-0.258	1.207	1.321
	(4.322)	(13.11)	(12.01)	(2.542)	(1.617)	(2.136)	(2.198)	(1.436)	(0.983)	(0.873)	(1.048)	(9.314)	(0.363)	(1.381)	(1.488)
Treatment X Cluster 3	0.865	3.498	0.802	4.429***	0.389	1.200	-1.928	1.322*	-0.299	0.0440	0.750	-8.739***	1.110**	1.830	0.0299
	(2.718)	(6.207)	(3.845)	(1.546)	(0.513)	(1.185)	(1.562)	(0.781)	(0.754)	(0.595)	(0.853)	(3.079)	(0.562)	(1.200)	(1.075)
Treatment X Cluster 4	-0.518	-4.623	4.518	3.189*	-0.893	0.961	-1.835	1.853	-0.103	0.623	1.618	0.177	-0.401	0.431	-0.240
	(3.764)	(9.530)	(9.805)	(1.909)	(0.654)	(1.733)	(1.657)	(1.947)	(1.131)	(0.658)	(1.391)	(3.884)	(0.395)	(0.417)	(1.384)
Cluster 2	0.758	-5.272	-1.862	-1.441	-0.718	-0.660	-0.589	-0.211	0.264	-0.113	-0.367	7.373	-0.305**	-1.622	-0.752
	(1.516)	(4.295)	(3.297)	(1.369)	(0.485)	(0.994)	(0.853)	(0.363)	(0.423)	(0.338)	(0.505)	(4.853)	(0.144)	(1.224)	(0.548)
Cluster 3	0.459	1.153	1.198	0.483	-0.158	0.199	0.785	-0.242	0.351	0.120	0.505**	3.503**	-0.0949	0.0913	0.523*
	(0.808)	(2.221)	(1.178)	(0.705)	(0.160)	(0.407)	(0.606)	(0.330)	(0.224)	(0.169)	(0.252)	(1.718)	(0.119)	(0.0753)	(0.270)
Cluster 4	2.845*	-2.949	3.236*	1.462	0.332	-0.373	-0.0643	0.154	0.363	-0.137	0.999*	3.040*	0.132	0.392	-0.277
	(1.615)	(4.908)	(1.914)	(1.032)	(0.219)	(0.490)	(0.482)	(0.438)	(0.265)	(0.179)	(0.519)	(1.632)	(0.199)	(0.265)	(0.339)
Observations	20,278	20,278	20,278	20,278	20,278	20,278	20,278	20,278	20,278	20,278	20,278	20,278	20,278	20,278	20,278
R-squared	0.189	0.405	0.437	0.186	0.250	0.144	0.394	0.209	0.220	0.0851	0.150	0.484	0.623	0.552	0.236
Treated hh	344	344	344	344	344	344	344	344	344	344	344	344	344	344	344
Control hh	356	356	356	356	356	356	356	356	356	356	356	356	356	356	356
Mean dep var	22.13	93.04	42.55	11.53	1.850	5.112	5.458	2.139	2.623	1.631	4.006	18.89	1.449	1.046	7.478

Notes: Appendix C describes how trips were classified. All regressions also include (not shown) controls for baseline levels of the dependent variable and interactions between that baseline and treatment. The omitted category is Cluster 1. *** p<0.01, ** p<0.05, * p<0.1.

E Extra tables

Table E.1: Unweighted daily average treatment effects

VARIABLES	(1) Trips (/day)	(2) Distance (km/day)	(3) Duration (min/day)
Treatment = 10c per km	-0.144*	-2.229**	-3.066**
	(0.0766)	(0.986)	(1.274)
Observations	148,160	148,160	148,160
R-squared	0.0298	0.00487	0.0133
Treated hh	354	354	354
Control hh	358	358	358
Mean dep var	3.373	32.20	51.57

Notes: Each column header represents a different dependent variable. They represent the following variables: Column (1): number of trips per day. Column (2): kilometers per day. Column (3): minutes traveled per day. Column (4) number of destinations, not including home, each day. All regressions include household fixed effects and date fixed effects. Standard errors are clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1.

Table E.2: Source of reductions in distance under distance charge

VARIABLES	(1) Distance	(2) Distance if drives	(3) Drives	(4) Destinations	(5) Destination-distance
Treatment = 10c per km	-2.055*	-0.857	-0.0370***	0.0528	0.193
	(1.060)	(1.107)	(0.0123)	(0.0475)	(0.922)
Observations	147,831	107,749	147,831	107,749	106,099
R-squared	0.00541	0.00858	0.0218	0.0230	0.00956
Treated hh	353	353	353	353	353
Control hh	356	356	356	356	356
Mean dep var	32.23	44.28	0.728	3.237	26.47

Notes: Column (1) shows the effect on daily distance driven (in kilometers/day) for the full sample. Columns (2), (4) and (5) restrict the sample in (1) to households observed driving on that day. The dependent variable in Column (3) is an indicator variable for whether a household drives at all on a given day. The dependent variable in Column (4) is the number of destinations visited on driving days. A round-trip loop counts as one destination. The dependent variable in Column (5) is the daily sum of as-the-bird-flies distances between home and each destination. We allocate the furthest point from home as the destination for all loops to and from home. All regressions include household fixed effects, date fixed effects, and inverse probability weights to address sub-treatment selection. Standard errors are clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1.

Table E.3: Top 25 congested roads

Panel (a): distance traveled (km/day)

VARIABLES	(1) Local	(2) Express	(3) Local	(4) Express	(5) Local	(6) Express
Treatment = 10c per km	-0.105	-0.0489				
	(0.0908)	(0.194)				
Treatment = 15c peak 8c off-peak			-0.158	-0.147		
			(0.0981)	(0.186)		
Treatment = 8c per km and cordon					-0.201*	-0.0125
					(0.104)	(0.199)
Observations	126,746	126,746	138,799	138,799	136,158	136,158
R-squared	0.00484	0.00349	0.00404	0.00299	0.00532	0.00301
Treated hh	353	353	344	344	329	329
Control hh	356	356	358	358	358	358
Mean dep var	1.476	1.949	1.441	2.026	1.439	1.986

Panel (b): time spent traveling (min/day)

VARIABLES	(1) Local	(2) Express	(3) Local	(4) Express	(5) Local	(6) Express
Treatment = 10c per km	-0.125	-0.0249				
	(0.188)	(0.162)				
Treatment = 15c peak 8c off-peak			-0.321	-0.108		
			(0.207)	(0.153)		
Treatment = 8c per km and cordon					-0.386*	-0.0223
					(0.207)	(0.168)
Observations	126,746	126,746	138,799	138,799	136,158	136,158
R-squared	0.00826	0.00355	0.00743	0.00327	0.00857	0.00360
Treated hh	353	353	344	344	329	329
Control hh	356	356	358	358	358	358
Mean dep var	3.143	1.539	3.093	1.603	3.078	1.591

Notes: Regressions restricted to travel on 25 most congested roads as defined by Austroads 2016. “Express” refers to CityLink, Monash Freeway, West Gate Freeway, and Western Ring Road. “Local” refers to the other 21 most congested roads. All regressions include household fixed effects and date fixed effects. The distance-charge regressions include inverse probability weights to address sub-treatment selection. Standard errors are clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1.

Table E.4: Baseline cordon entry by income (all treatments)

Annual Income	HH weekdays (1)	Cordon entries (2)	% HH weekdays (3)	(4)	% Cordon entries (5)	(6)
Less than \$20,800	4917	179	6	6	4	4
\$20,800 to \$41,600	10026	215	12	18	5	9
\$41,600 to \$65,000	10760	285	13	30	6	15
\$65,000 to \$104,000	16106	1066	19	49	23	38
\$104,000 to \$156,000	12362	895	15	64	20	58
Greater than \$156,000	10031	1002	12	76	22	80
Did not say	20304	932	24	100	20	100

Notes: Column (1): Number of baseline household-weekdays in our sample for each income group. Column (2): Number of household-weekdays with cordon entries in that period for each income group. Columns (3) and (4): Percentage and cumulative percentage of total household weekdays by that income group. Columns (5) and (6): Percentage and cumulative percentage of cordon entries by that income group.

Table E.5: Elasticity of travel demand by income, variation induced by distance charge

VARIABLES	(1) < 20.8k	(2) 20.8 - 41.6k	(3) 41.6 - 65k	(4) 65 - 104k	(5) > 104k	(6) NA
lprice	-0.5671**	-0.1458	-0.1454	0.0699	-0.0814	-0.2088**
	(0.254)	(0.147)	(0.124)	(0.105)	(0.076)	(0.106)
Observations	1,111	2,231	2,754	3,640	5,204	4,752
R-squared	0.0772	0.0330	0.0742	0.0274	0.0326	0.0310
Treated hh	23	41	45	61	94	89
Control hh	20	36	52	69	89	78
CDW F-test	1227	1228	1274	1637	3235	2430

Notes: Regressions of log price on log distance estimated via TSLS using active treatment status as an instrument for price. All regressions include household fixed effects and date fixed effects and inverse probability weights to address sub-treatment selection. Standard errors are clustered at the household level. hh = households. *** p<0.01, ** p<0.05, * p<0.1.

Table E.6: Price elasticity by type of low-income household

VARIABLES	(1) Age<65	(2) Age≥ 65	(3) Employed	(4) Unemployed	(5) Close train	(6) Far train
log price, Distance charge	-0.3307**	-0.1133	-0.3232***	-0.1259	-0.3153**	-0.2006
	(0.146)	(0.120)	(0.112)	(0.142)	(0.129)	(0.127)
Observations	3,073	2,987	3,166	2,930	2,157	3,906
R-squared	0.0695	0.0386	0.0842	0.0388	0.0724	0.0424
Treated hh	48	59	54	55	45	64
Control hh	60	48	56	52	37	70
CDW F-test	1617	1717	1878	1543	1395	1996

Notes: Regressions of log price on log distance estimated via TSLS using active treatment status as an instrument for price. Employment status was recorded in the recruitment survey, and supplemented in a few cases by clear observed patterns of work commutes. Close to a train station reflects a household SA1 being located less than 1 kilometer from a train station. All regressions include household fixed effects and date fixed effects and inverse probability weights to address sub-treatment selection. Standard errors are clustered at the household level. hh = households. *** p<0.01, ** p<0.05, * p<0.1.

Table E.7: Treatment effects and cordon entry by distance from public transport

Panel (a): Distance traveled (kilometers/day)

VARIABLES	(1) 0 to 0.5km	(2) 0.5 to 1km	(3) 1 to 1.5km	(4) 1.5 to 3.5km	(5) 3.5 to 34km
Treatment = 10c per km	-2.684*	-0.877	1.452	-1.681	-5.892**
	(1.394)	(1.775)	(1.660)	(3.501)	(2.821)
Observations	29,484	29,964	29,551	29,352	28,504
R-squared	0.0153	0.0132	0.0154	0.0182	0.0184
Treated hh	76	75	70	69	63
Control hh	71	65	74	66	75
Mean dep var	26.05	29.17	27.55	39.81	39.04

Panel (b): Distance traveled at peak times (kilometers/day)

VARIABLES	(1) 0 to 0.5km	(2) 0.5 to 1km	(3) 1 to 1.5km	(4) 1.5 to 3.5km	(5) 3.5 to 34km
Treatment = 15c peak 8c off peak	0.309	-2.680***	-0.585	-1.794	-1.447
	(0.983)	(0.952)	(1.008)	(1.732)	(1.137)
Observations	27,405	28,252	26,493	27,873	27,800
R-squared	0.0958	0.125	0.166	0.149	0.150
Treated hh	72	77	61	69	65
Control hh	71	65	74	67	76
Mean dep var	8.431	9.337	10.42	12.79	12.26

Panel (c): Cordon entry (/day)

VARIABLES	(1) 0 to 0.5km	(2) 0.5 to 1km	(3) 1 to 1.5km	(4) 1.5 to 3.5km	(5) 3.5 to 34km
Treatment = 8c per km and cordon	0.00835	-0.0733*	0.0754*	-0.0110	-0.0545
	(0.0302)	(0.0408)	(0.0433)	(0.0208)	(0.0462)
Observations	12,261	8,377	7,218	9,252	6,246
R-squared	0.0219	0.0336	0.0320	0.0224	0.0342
Treated hh	46	31	31	37	19
Control hh	44	29	24	30	26
Mean dep var	0.146	0.146	0.0933	0.0774	0.0709

Notes: All regressions include household fixed effects and date fixed effects. The time-of-day regressions are restricted to peak times (7-9am and 3-6pm Monday-Friday). The cordon entry regressions are restricted to weekdays and households that ever entered the cordon during baseline. The distance-charge regressions includes inverse probability weights to address sub-treatment selection. Standard errors are clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1.

Table E.8: Driving to train stations

VARIABLES	(1)	(2)	(3)
Treatment = 10c per km	-0.00124		
	(0.0130)		
Treatment = 15c peak 8c off-peak		-0.0124	
		(0.0214)	
Treatment = 8c per km and cordon			-0.0228
			(0.0209)
Observations	21,677	21,420	21,346
R-squared	0.0291	0.0225	0.0243
Treated hh	52	58	57
Control hh	50	52	52
Mean dep var	0.0666	0.0633	0.0633

Notes: Dependent variable is an indicator variable for whether a household commutes to a rail station on a given day, either by parking in the station parking lot or dropping someone off at a station. It is restricted to households living greater than 1km from a public transit station. For dropoffs we only consider loops to and from home whose sole purpose appears to be a station pickup or dropoff. Regression is restricted to households ever observed driving to a rail station. All regressions include household fixed effects and date fixed effects. The distance-charge regression in column (1) includes inverse probability weights to address sub-treatment selection. Standard errors are clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1.

Table E.9: Marginal effects from multinomial logit model

	(1)	(2)	(3)
VARIABLES	A	B	C
Trips per day	-0.0545***	0.0252	0.0294*
	(0.0176)	(0.0175)	(0.0172)
Distance (km/day)	0.00336**	-4.79e-05	-0.00331*
	(0.00163)	(0.00173)	(0.00177)
Time spent driving (minutes/day)	0.00103	-0.000621	-0.000406
	(0.00135)	(0.00142)	(0.00141)
Fraction driving at peak	0.115	-0.222	0.107
	(0.134)	(0.141)	(0.135)
Distance to CBD (km)	0.00313***	-0.00125	-0.00189*
	(0.00109)	(0.00115)	(0.00114)
Multiple Cars (=1)	0.0207	-0.00164	-0.0191
	(0.0335)	(0.0336)	(0.0328)
Household Size	-0.0241	-0.00632	0.0305*
	(0.0179)	(0.0177)	(0.0170)
Has Kids u18 (=1)	-0.00418	0.0564	-0.0523
	(0.0462)	(0.0468)	(0.0443)
Vehicle fuel efficiency (liters/100 km)	-0.00937	0.0125*	-0.00310
	(0.00745)	(0.00734)	(0.00727)
Vehicle year	-0.00173	0.00365	-0.00192
	(0.00346)	(0.00352)	(0.00336)
Observations	1,017	1,017	1,017

Notes: All variables based on baseline period only. Standard errors are clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1.

Table E.10: Elasticity by number of cars parked overnight

VARIABLES	(1) Distance Multicars	(2) One car	(3) Time of Day Multicars	(4) One car
log price	-0.0659	-0.1785**	0.0021	-0.1768**
	(0.064)	(0.072)	(0.086)	(0.090)
Observations	10,007	9,588	9,388	8,853
R-squared	0.0226	0.0351	0.0284	0.0366
Treated hh	178	174	176	168
Control hh	170	172	170	172
CDW F-test	4854	5858	4396	4440

Notes: Regressions of log price on log distance estimated via TSLS using active treatment status as an instrument for price. All regressions include household fixed effects and date fixed effects and inverse probability weights to address sub-treatment selection. Standard errors are clustered at the household level. hh = households. *** p<0.01, ** p<0.05, * p<0.1.

Table E.11: Attrition rates (percentages) within each phase by date

	Control - Phase 1 pcent/d/se	Distance charge pcent/d/se	Control - Phase 2 pcent/d/se	Cordon Distance pcent/d/se	TOD Distance pcent/d/se
Exits before day 30	1.67	0.28	2.51	2.43	2.91
		-1.39*		-0.075	0.40
		(0.74)		(1.19)	(1.23)
Exits before day 40	1.95	0.56	4.74	3.65	4.07
		-1.38*		-1.09	-0.67
		(0.84)		(1.54)	(1.55)
Exits before day 50	2.79	0.85	6.69	4.86	5.23
		-1.94*		-1.82	-1.45
		(1.00)		(1.79)	(1.79)
Exits before day 60	3.90	1.41			
		-2.49**			
		(1.20)			
Exits before day 70	5.85	1.98			
		-3.87***			
		(1.45)			
Exits before day 80	8.36	1.98			
		-6.38***			
		(1.65)			

Notes: Standard errors clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1. Abbreviations: pcent = percentage attrition rate, d = percentage point difference in means and se = standard errors.

Table E.12: Difference in mean travel account balances in prior month of attritors versus non attritors

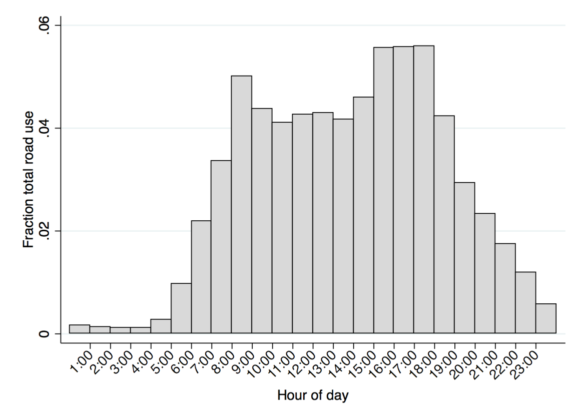
	Non Attritors phase one avg/sd	Attritors phase one diff/se	Non Attritors phase two avg/sd	Attritors phase two diff/se
Prior Month Travel Account Balance	34.6	0.65	80.4	-6.45
	[42.7]	(12.4)	[81.2]	(13.5)

Notes: Standard errors clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1. Abbreviations: avg = mean balance in month prior, sd = standard deviations, diff = difference in means and se = standard errors. Standard deviations in square brackets, standard errors in parentheses.

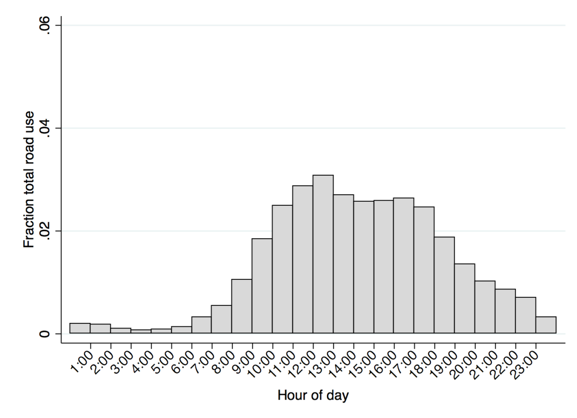
F Extra figures

Figure F.1: Baseline distance traveled by hour of day

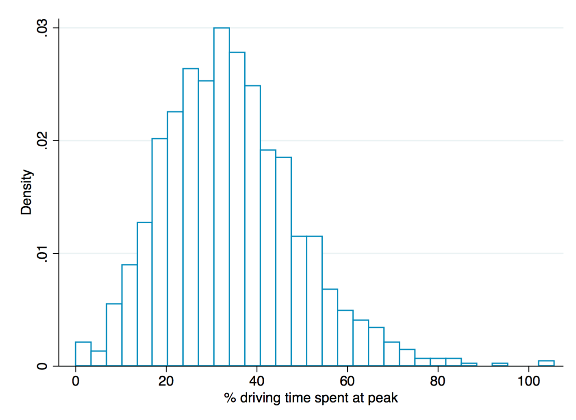
(a) Distance by hour of day, weekday



(b) Distance by hour of day, weekend

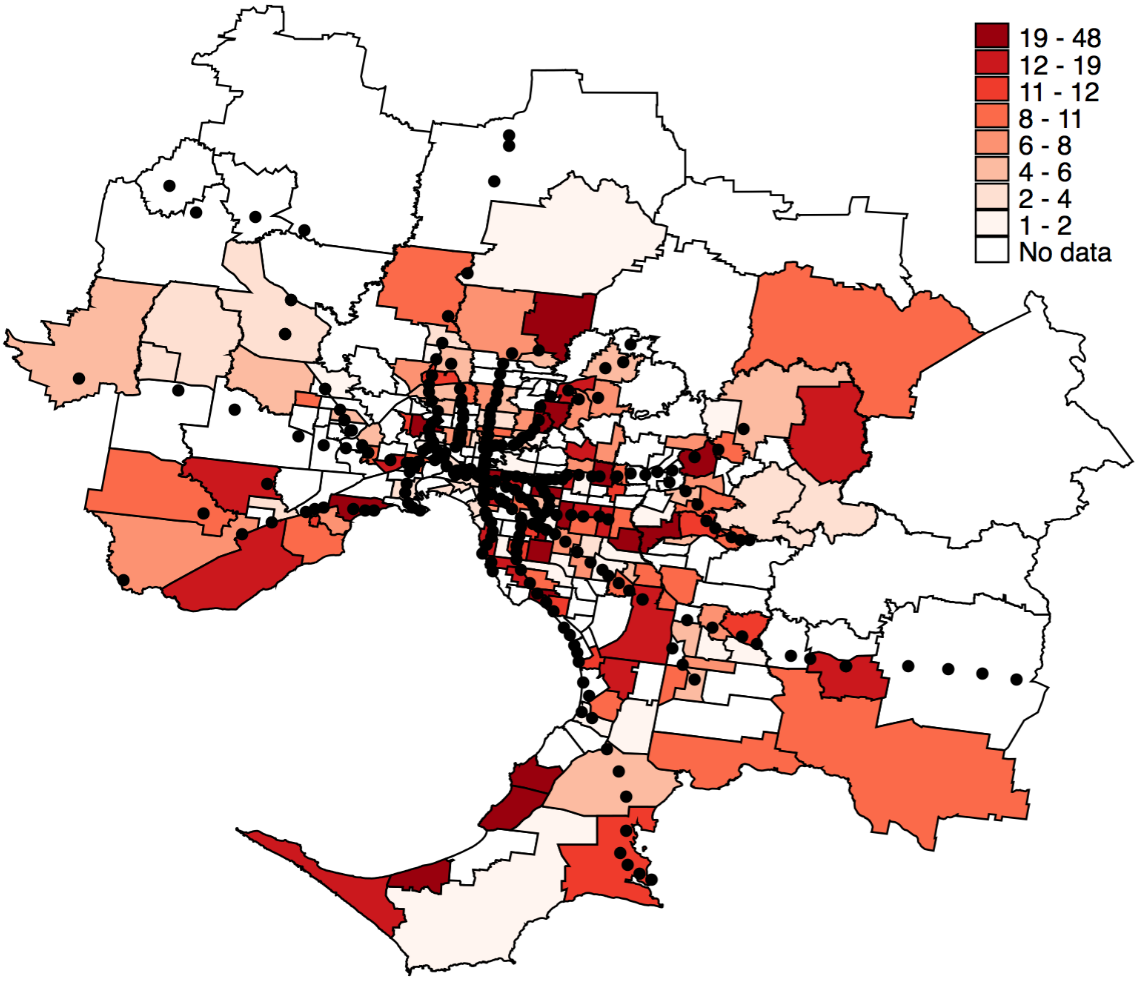


(c) Heterogeneity in fraction of driving at peak



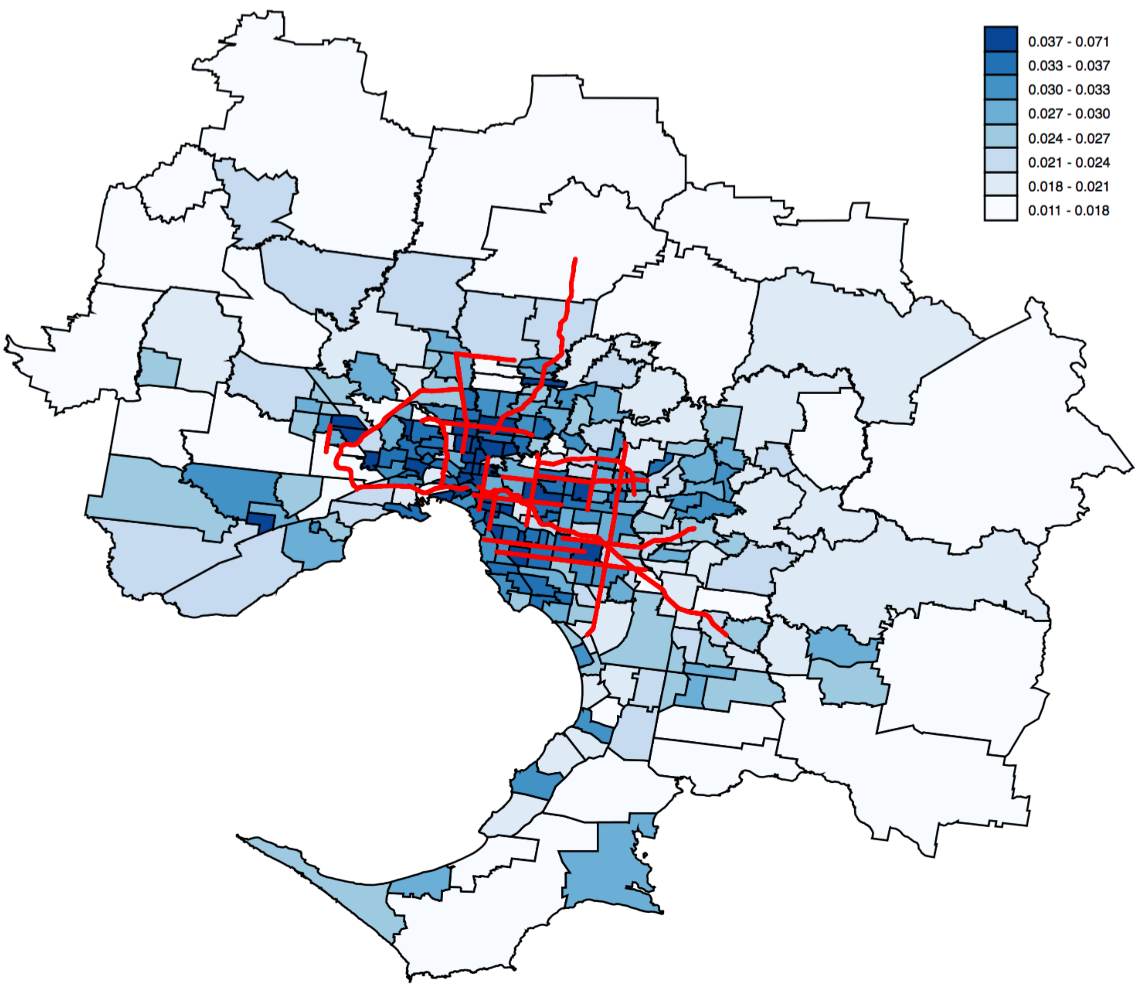
Notes: Panels (a) and (b) represent kilometers traveled by all households by hour of day and weekday/weekend during baseline period. Panel (c) represents percentage of the time a household spends driving at peak times during the baseline period. Peak is Monday-Friday 7-9am and 3-6pm.

Figure F.2: Geographical distribution of households in experiment



Notes: Number of households by census statistical area (SA2, one level higher than level used in analysis) and rail stations (black dots), highlighting distance to the CBD and rail stations. Our analysis also includes tram stations.

Figure F.3: Distribution of congestion: average speeds and Top 25 most congested roads



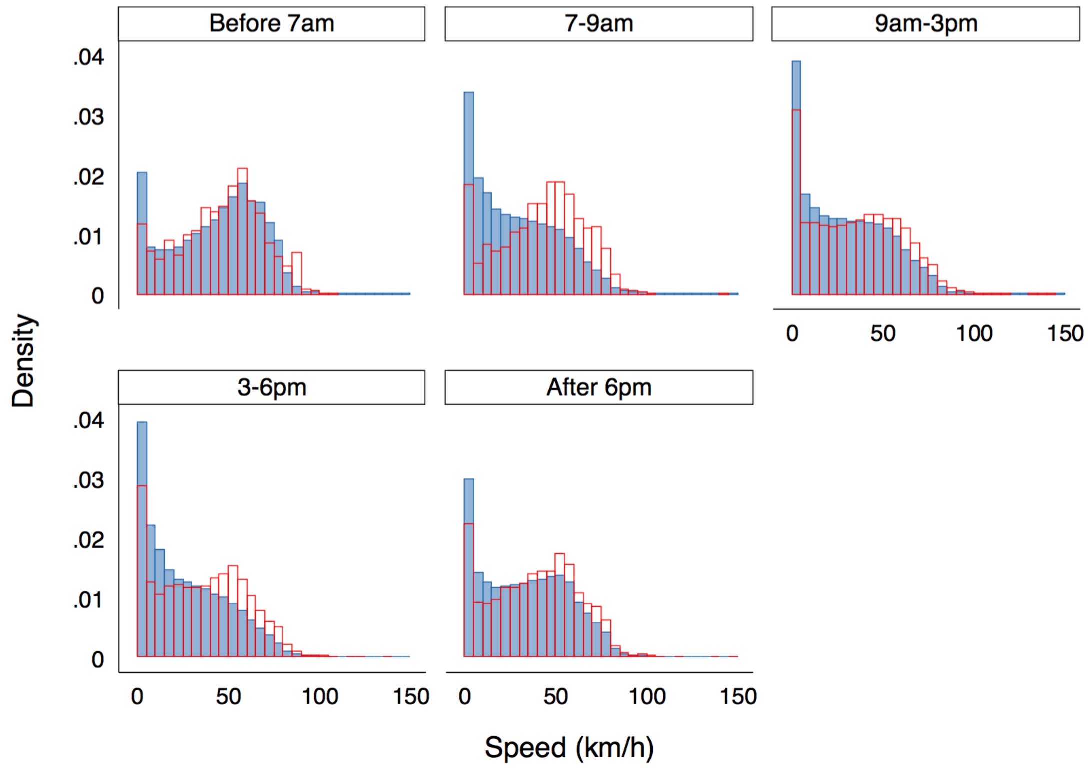
Notes: Blue shades represents the inverse of the average speed observed during baseline in each census statistical area (SA2, one level higher than level used in analysis). A darker shade represents a slower speed, i.e. higher congestion or a larger share of driving taking place on roads with lower speed limits. The 25 red lines represent the 25 most congested roads in Melbourne according to Austroads 2016.

Figure F.4: Average speeds (km/hr) on congested arterial roads during baseline

	Speed (km\hr)									
	Monday - Friday					Saturday - Sunday				
	Before 7am	7-9am	9am-3pm	3-6pm	After 6pm	Before 7am	7-9am	9am-3pm	3-6pm	After 6pm
Inner cordon										
Cordon border										
Outer cordon										
Hotham Street	27.7	19.5	25.7	22.6	26.5	34.4	34.3	25.2	25.7	29.7
Punt Road	30.1	15.8	19.2	17.4	22.3	33.2	31.5	20.6	19.8	23.8
Williams Road	31.5	23.9	22.3	21.3	25.8	34.8	30.3	21.7	23.1	28.2
Station Road	32.0	26.0	33.4	27.5	35.1	43.0	52.5	31.5	32.6	31.9
Hoddle Street	32.0	18.0	20.6	17.3	23.1	30.0	30.4	21.3	21.0	24.6
Cooper Street	33.4	34.7	28.5	29.9	38.8	36.8	46.0	34.0	35.2	42.8
Ferntree Gully Road	34.0	33.9	36.5	34.7	41.6	52.3	45.3	39.5	41.7	46.7
Toorak Road	34.4	20.4	20.0	17.7	24.4	32.8	28.8	21.2	22.4	26.5
Police Road	34.9	22.1	23.3	22.8	29.6	35.9	32.6	24.0	28.1	33.7
Doncaster Road	35.1	27.5	25.1	25.2	27.7	38.0	31.1	26.3	26.2	31.0
Bell Street	36.2	30.6	29.1	26.2	36.6	42.6	42.3	30.7	32.8	38.5
Sydney Road	36.4	27.3	23.5	22.5	29.3	39.4	28.9	24.6	25.6	30.7
Middleborough Road	36.8	28.0	25.1	21.7	30.7	43.4	32.0	25.0	26.7	35.6
Burke Road	38.9	23.9	25.5	21.4	31.2	39.4	34.5	26.9	28.6	33.1
Centre Road	39.1	23.2	20.6	19.8	24.3	33.9	29.7	21.1	22.0	25.5
Barkers Road	39.2	18.7	25.1	21.0	25.7	40.3	29.4	25.7	26.1	31.3
Mitcham Road	40.9	33.6	35.1	34.2	35.4	48.2	37.6	36.7	38.9	41.4
Springvale Road	42.4	27.8	28.6	26.1	34.7	45.1	38.5	30.0	31.8	37.9
Whitehorse Road	42.6	29.1	25.4	25.6	32.7	44.4	34.3	28.0	31.6	36.3
North Road	45.4	27.5	29.6	24.5	29.8	42.1	34.7	29.3	30.0	32.7
Plenty Road	53.7	42.6	44.7	39.1	47.8	58.7	50.7	43.9	45.7	52.7

Figure F.5: Top 25 congested roads: observed speeds (blue = Monday-Friday, red=public holiday)

(a) Local roads



(b) Express roads

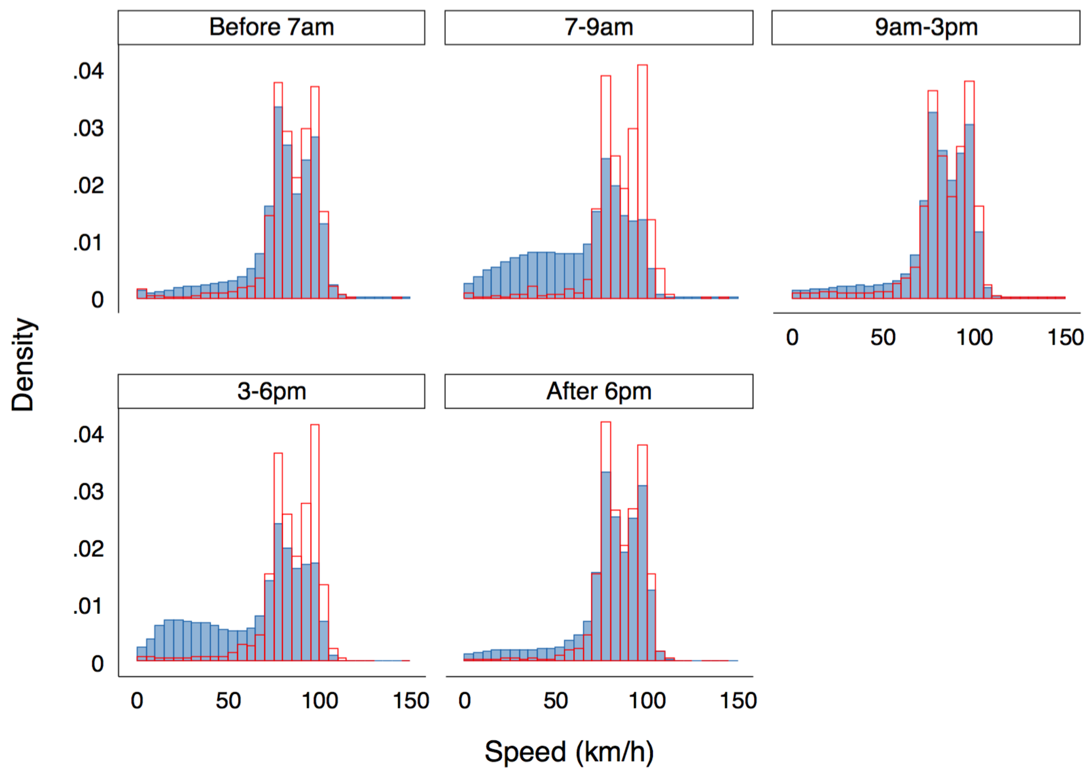
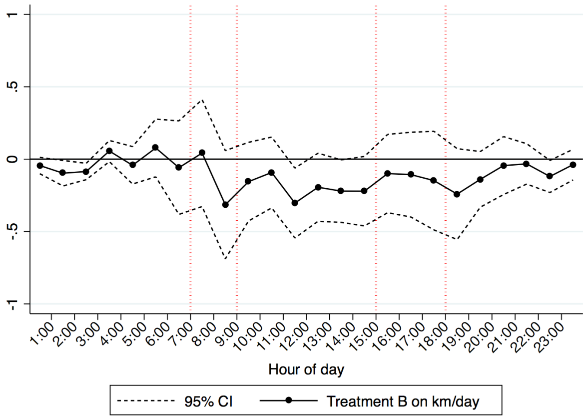


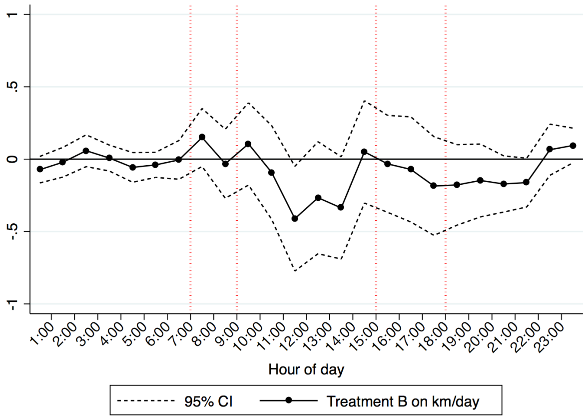
Figure F.6: Effect of road use charge on daily distance traveled, by time of day

Uniform VMT charge

(a) Monday-Friday

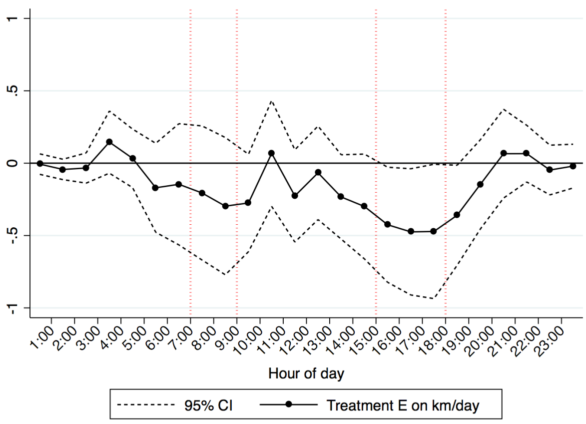


(b) Saturday-Sunday

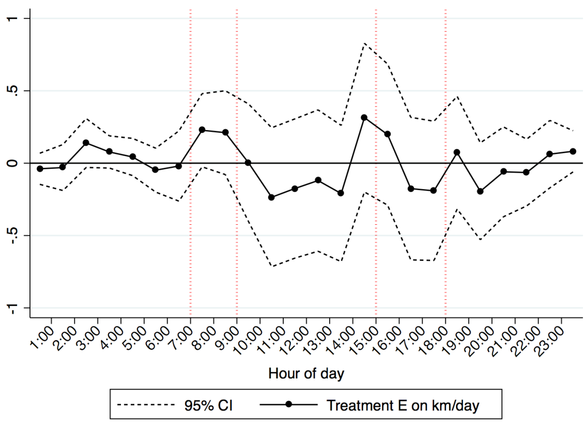


Time-of-day VMT charge

(c) Monday-Friday

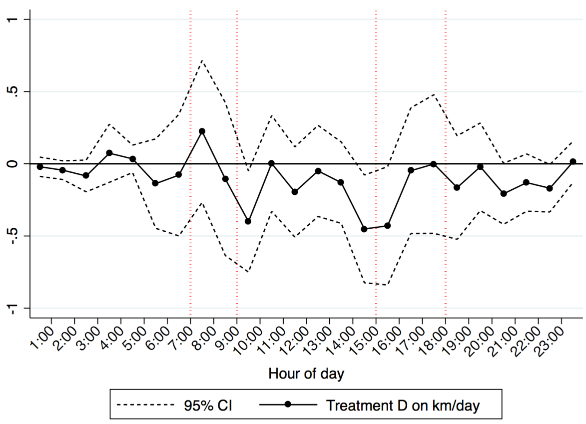


(d) Saturday-Sunday

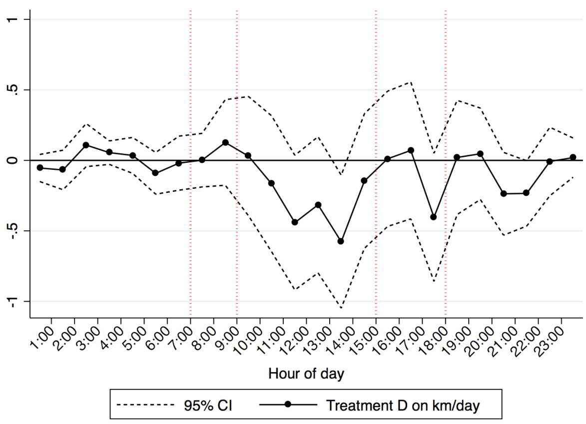


Uniform VMT and cordon charge

(e) Monday-Friday



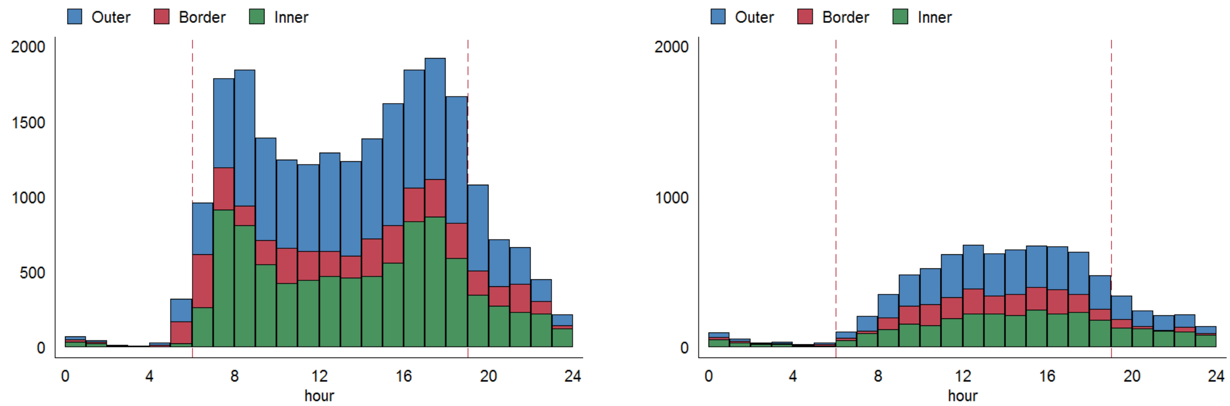
(f) Saturday-Sunday



Notes: The dependent variable is kilometers per day at the given hour interval. Panel (a) represents the effect the per kilometer charge of 10c per kilometer. Panel (b) represents the effect of the time-of-day charge of 15c per kilometer peak, 8c per kilometer off-peak. Peak is 7-9am and 3-6pm Monday-Friday. Panel (c) represents the effect of the uniform VMT of 8c per kilometer plus $8 per day for cordon entry. Black dashed lines are 95% confidence intervals.

Figure F.7: Baseline cordon use: number of driver-days with trips into cordon

(a) Monday-Friday (b) Saturday-Sunday



Notes: Number of baseline days with trips into cordon, out of a total of 64,282 weekday and 25,546 weekend driver-days (up to 593 drivers over 216 days). Bars are overlaid, not stacked.

Figure F.8: Overlap in propensity scores

(a) Treatment A (b) Treatment B

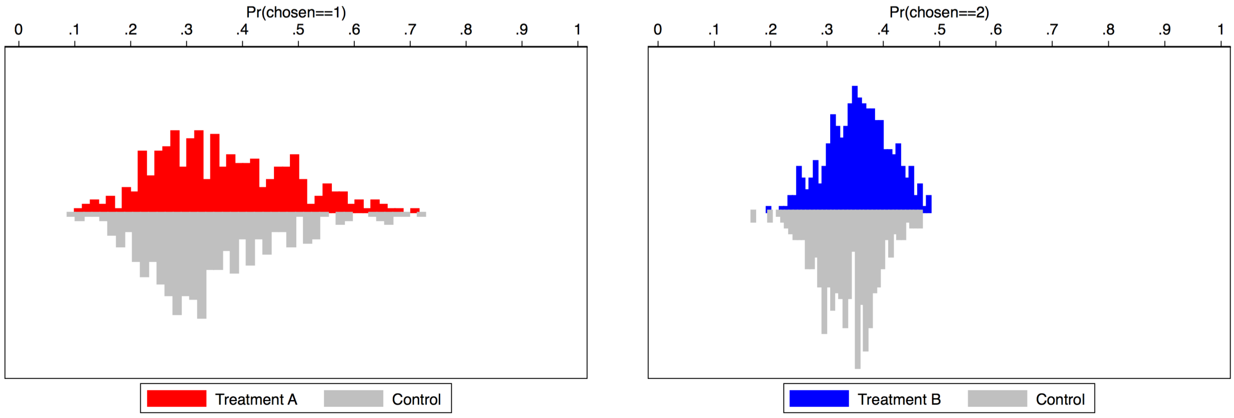


Figure F.9: Conditional densities for probability of treatment

(a) Treatment A (b) Treatment B

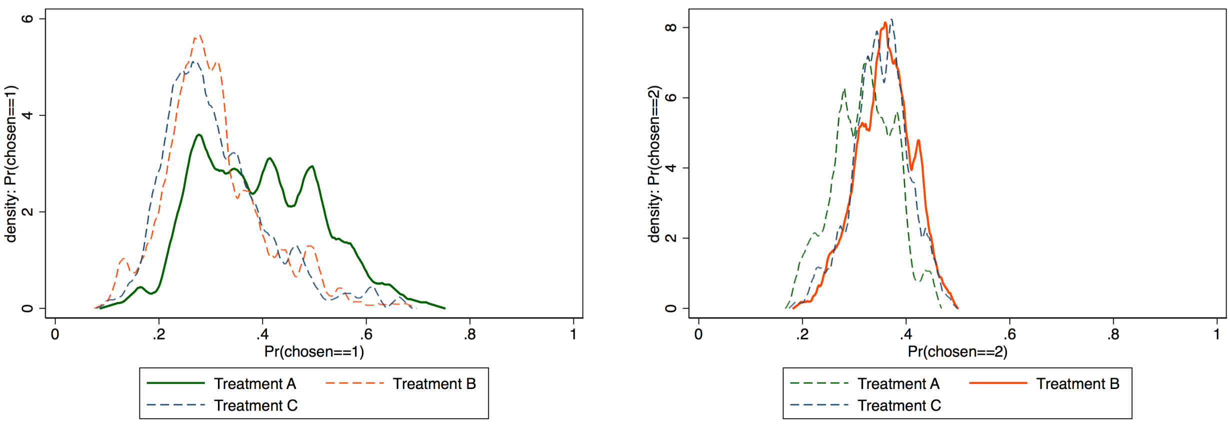
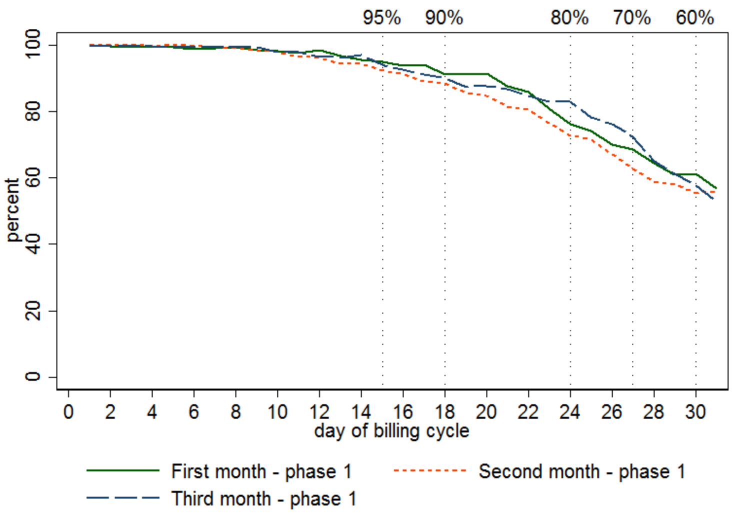


Figure F.10: No evidence of end-of-cycle reversal of driving reduction

(a) Percentage of households with positive balance during billing cycle - distance-based charge



(b) Treatment effect for treatment B excluding observations later in billing cycle

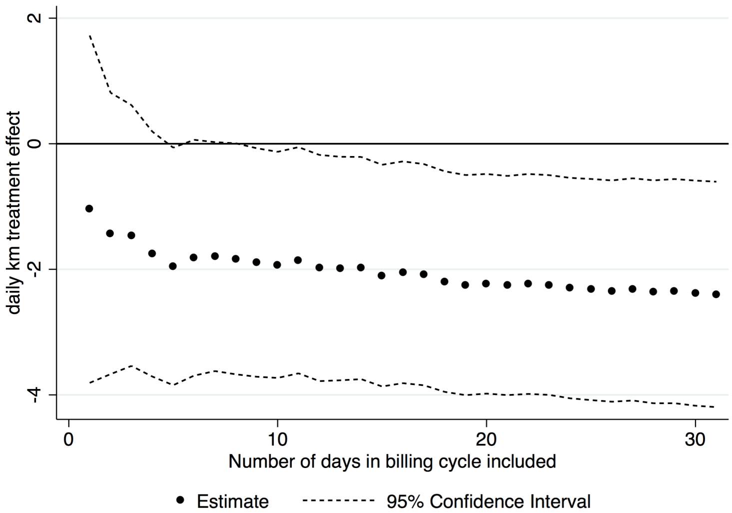


Figure F.11: Travel account balances in prior month

(a) Phase 1 - Treatment

(b) Phase 2 - Time of Day and Cordon Treatments