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

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Abstract

We describe the results of a large road use pricing experiment that installed GPS responders in 1400 vehicles and implemented usage, time-of-day, and cordon charges via a system of virtual accounts. Using six-second location data collected over an eight to ten month period, we find a mean price elasticity of -0.13 to per kilometer charges, which is consistent with the literature on short-term demand response to fuel price increases. We find that uniform road use 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 congested road conditions. We also document the role of public transit, providing evidence that time-of-day and cordon charges push out the distance between home and station at which households opt to walk and ride. We observe households that do chose to drive reducing distance traveled by linking destinations. We see no increase in driving to commuter rail and no reduction in commutes to work. Finally, we show that because low-income drivers drive less and respond more, they benefit the most from replacing existing sources of road revenues 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) show that the long-run elasticity of demand to an increase in road lane-kilometers and public transport infrastructure is almost one-to-one. Demand-based measures like road use charges, however, have potential. William Vickrey started advocating for congestion-based road charges on economic efficiency grounds over 50 years ago (Vickrey (1963), Vickrey (1969)). He pointed out that when roads are congested, each additional driver lowers the speed for other drivers. Charges that reflect the cost that individual drivers impose on the system can encourage some drivers to shift to less congested times or other modes or routes. If designed well, road use charges could increase how efficiently the transportation system is used, cutting travel times and minimizing the disruption caused by unexpected delays.

Road use charges can take several forms. Road-access tolls can vary with time of day (San Francisco's Bay Bridge) or road conditions (express lanes near San Diego and Los Angeles). Several cities have imposed charges for accessing or using an entire geographical area (Singapore, London, Stockholm, Milan). Finally, some systems charge for using the road network regardless of where drivers use it via distance-based charges (New Zealand, Oregon). These systems vary in how closely prices reflect current road conditions.

The recent interest in congestion charges has been driven by technology. Electronic tolling dramatically reduces the cost of implementing road use charges. But widespread adoption is hindered by a public concern that congestion-based charges are unfair (Linn et al. (2016)). Households in areas with inadequate provision of public transport alternatives face higher costs of substitution. And there is a fear that congestion pricing would "price the poor off the road" for the convenience of the wealthy. Are road use charges really more regressive than our current system of transport charges?

This paper examines how drivers respond to different types of road use charges. Do they reduce driving under congested conditions? And, if so, who bears the cost. We use a large road pricing experiment that installed GPS devices in the primary vehicles of 1400 households in a large metropolitan area of 4.7 million people for eight to ten months. 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.

The time costs of road congestion are by far the biggest externality in road transport, much larger than the costs of pollution (Parry and Small (2005)). Parry and Small propose a tax on

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

kilometers traveled as an alternative to fuel taxes in order to better target the primary externality. We concur that policies directly targeting congestion outperform fuel taxes. And we show in this paper that a tax on distance traveled is unlikely to be not targeted enough.

We find that although a constant 10 cents per kilometer fee reduces driving, it is unlikely to reduce congestion because households respond primarily by reducing driving under un-congested conditions. The trips not taken are those that fall in the middle of the day and on weekday evenings, whereas most congestion occurs around morning and late afternoon commutes. Furthermore, most reductions in driving occur well outside the congested downtown area, without decreasing use of highly congested local arterial roads. Most critically, we show that most of the reductions occur from trip micro-segments with average travel speeds of 50-75 km/hour, representing uncongested road conditions.

Charges that vary by time of day or location are more likely to reduce congestion. We consider a treatment where weekday commuting 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, with lower overall reduction than on a time-invariant distance plan. 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, but these reductions occur primarily on weekends, which were not targeted, and are less congested.

Finally, we show that under revenue recycling the burden of congestion pricing does not fall on the poor or elderly. 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.

This paper makes several contributions to the literature. It is the first paper to use GPS transponders to study how driving patterns respond to road pricing. Until now road pricing research has primarily focused on aggregate traffic flows (Gibson and Carnovale (2015) and Foreman (2016)), self-reported travel diaries (Karlström and Franklin (2009)), or self-reported behavior from telephone surveys (Small et al. (2005)). 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.

With the additional resolution provided by the GPS devices, we are able to comment on who responds to road use prices, when, and on what types of trips. By knowing when drivers adjust, we provide evidence that distance-based charges that do not distinguish by time or location will reduce driving at times and locations that do not, in a partial equilibrium setup, lead to reductions in congestion. Half of the reductions in road use from distance-based charges are from households increasing the number of days when they don't drive at all. On days that they do drive, they also drive less, not by reducing the number or types of destinations visited, but instead by linking trip segments together. We document that work commutes are completely inelastic to the increase in the marginal cost of driving. By knowing who responds, we are able to parse responsiveness by disadvantage, specifically income and lack of access to public transport.

This paper is also one of the first two papers to experimentally allocate road use charges. The experimental variation in costs 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 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.

A parallel paper, Kreindler (2017), provides commuters in Bangalore with incentives to avoid starting commutes at peak times and monitors compliance via a smart phone app. His paper uses a research design that allows him to estimate how much individual drivers value their time and being on time.

A few papers have used aggregate traffic flows to study time-of-day pricing and cordon charges. Although these studies lack the driver- and trip-level resolution that ours provides, they capture general equilibrium effects as drivers re-optimise given new expectations of travel times. Like Foreman (2016), who studies the introduction of time-varying tolls on the San Francisco Oakland Bay Bridge, we finds evidence of reduction in driving during peak times. Unlike her, however, we find no evidence of substitution from peak to off-peak times. Leape (2006) finds that the London congestion charging scheme led to time savings and increased reliability. Gibson and Carnovale (2015) also show that, under a cordon charge in central Milan, drivers reduced entry into the cordon area, drove more on nearby unpriced roads, and substituted trips to unpriced times. Most of our cordon entry is driven by a small set of relatively high-income households. The reductions that we observe come from households living a 10 to 20 minute walk away from public transit. The evidence points towards these households switching modes rather than adjusting routes or changing times.

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 income and age gradients using household-specific income and age and GPS measures of road use. We find similar results: low-income households are more price elastic, which mitigates the loss in consumer surplus associated with higher per kilometer prices. We also document the role of public transport, providing evidence that time-of-day and cordon charges push out the distance between home and station at which households opt into the use of public transport.

The paper proceeds as follows. Section 2 describes the MRUS experiment and Section 3 presents baseline data. Sections 4 and 5 explain our empirical strategies and discuss results. 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. It lasted eight to ten months: three months of baseline driving followed by three months in the first treatment phase and then two months in the second treatment phase, with short untreated periods in between.

Participants were randomly selected from three geographical zones within the Greater Melbourne region. Melbourne is similar to the Greater Boston metropolitan area in population and area. 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] 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. 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]

From the sample of participants, over 900 households were randomly selected for treatment. A control group of over 300 participants did not experience any of the charging options. After several months of baseline travel, treated households were offered the option of one of three pricing treatments (trip-based, distance-based, or flat rate) for three months. We discuss the sub-treatment selection in this phase and how we account for it in sections 3 and 5.5, respectively. Each sub-treatment had a limited number of slots, so households that were recruited later had fewer options. There was a minimum of 30 days of baseline un-treated driving for every treated household; the average baseline period was 94 days.

Treatment was rolled out progressively across households based on recruitment date, which was randomly assigned. The first 675 households to be offered treatment were then randomly-allocated to a second congestion-based sub-treatment (distance by time-of-day or distance and cordon) for another two months. There was a short untreated period of a few weeks between the two treatments. There was also a brief untreated period at the end of the second treatment that we drop in the

[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 located over 40 kilometers away from the CBD, placing them in the top 90th percentile of distance from the CBD.

analysis.

The treatments in the first phase were either priced by distance, at 10 cents per kilometer, per trip, at $1 per trip,[6] or at a "flat rate". The flat rate plan applied no charge for first X_i kilometers, where the number of free kilometers allocated each month was household-specific and calculated based on their baseline use. The flat rate plan then applied 20 cents per kilometer for all excess kilometers. All charges applied to all driving, not just driving on toll roads.

In the second phase, 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 1.

The treatments were applied via a system of virtual travel 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 the balance in real time via a web portal. The final balance was paid out at the end of the study. All participants were also provided a $100 gift card on joining 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 includes 43 million location coordinates and time stamps, representing readings taken every 6 to 30 seconds. All observations within each household's privacy cordon are 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 37 observations out of a total of over 1.2 million trips that reported time stamps with stop times before start times, and 78 observations with time stamps that implied average trip speeds that exceeded 120 kilometers per hour. We also dropped treatment households that attrited

[6] Vehicle movement is defined as a trip if the vehicle travels more than 100 meters after being stopped for at least five minutes.

during the baseline period and control households that attrited before 1 May, 2016.[7]

To identify trips and distances to train and rail, we obtained the locations of all train and tram stations from Public Transport Victoria, along with the shapefiles of all train station parking lots.

To identify work commutes we flag all destinations reached between 6am and 10am Monday through Friday where the vehicle remains parked between 5 and 15 hours. If that destination is a commuter rail parking lot we flag the trip to get there as a rail commute. If it is not, then we call the trip a potential workplace commute. For a given household, 75% of the destinations that we flag for a workplace commute involve endpoints within 100 meters of each other. In our main specification these workplace commutes are the only trips that we count as commutes. We flag all trip segments between the home and the commute destination, and back, as a commuting trip. Our algorithm implies that if a driver goes shopping on the way home from work, the driving between the shops and home will also be flagged as a work commute.[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 I and II 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 (10.2 kilometers per trip instead of 12.8) but at slower average speeds (25.8 kilometers per hour relative to 38.5), so average trip duration is slightly longer (22.2 minutes per trip instead of 17.5).

To look at which roads were most affected, 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 B.1 in the Appendix. We show that average speeds observed on these roads by vehicles in our sample by time of day (Figure B.2) and the distribution of speeds by time of day and whether the day is a regular weekend or public holiday (Figure B.3). 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.

Figure 2 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 (b)). Most households in our sample live within 10 kilometers of a commuter rail station; 75% live

[7]Most of these 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.

[8]This distinction is minor because 97.5% of morning and 98% of evening commutes are non-stop trips from and to the home, where a stop is defined as being parked for more than 5 minutes.

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

within 4 kilometers and 25% live within a kilometer (0.6 miles), i.e. potentially within walking-distance (Panel (c)). 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 (Panel (d)).

Table I shows that the treatment and control groups are balanced in the aggregate. The 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, who lived 3.8 kilometers away. Table II 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 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 the per trip charge and the 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 run all regressions using household fixed effects and all regressions for first phase sub-treatments using inverse probability weights. The weights help us compare each treated subgroup to a subset of the control group that is likely to have similar sub-treatment preferences. We find that our weighted results change very little relative to unweighted regressions.

We estimate daily treatment effects using a difference-in-differences specification with GPS data from the baseline and treatment periods. These regressions take the form:

$$y_{it} = \alpha_k \text{Treatment } k_{it} + \mu_i + \tau_t + \epsilon_{it} \tag{1}$$

where y_{it} is kilometers traveled, trips taken, minutes spent driving, or number of destinations by household i in day t. Treatment k is an indicator variable that takes on a value of 1 if household i is treated with sub-treatment k at time t and is otherwise 0. Each sub-treatment is estimated separately relative to the entire control group. α_k is the treatment effect, μ_i are household fixed effects, τ_t are date fixed effects, and ϵ_{it} is a residual error term.[10] In all specifications we cluster standard errors at the household level. We adjust for sub-treatment selection for the distance

[10]We also estimate the cordon and time-of-day treatments using random effects and find very similar results.

charge treatment using inverse probability weights, as explained in section 5.5. Table B.1 in the online appendix shows unweighted results, which are very similar.

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:

$$\log(q_{it}) = \eta_k \log(\text{travel cost}_{ikt}) + \mu_i + \tau_t + \epsilon_{it} \tag{2}$$

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.

5 Response to road user charges

5.1 Distance-based charges

Panel (a) of Table III 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 B.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 III 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 4 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 5 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 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.

5.2 Charges targeted at time of day

We then estimate the treatment effects for the distance by time-of-day charges. As shown in Table IV 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.

[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.

Furthermore when we look at the reduction in distance traveled by hour of day (Figure 6) 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 B.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 7 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.

5.3 Charges targeted at location

We then estimate the treatment effects for the distance plus cordon charge and present the results in Table V. 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 8. We also find that drivers are spending less time driving at all speeds below 55 km per hour (Figure 9).

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 VI). It appears that the distance that households are willing to walk to access public transit increases with the higher charges.

In Table V 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 B.4) 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.

5.4 Who responds

The evidence on the heterogeneity in demand response by level of income is mixed. Wealthier drivers may be more sensitive to changes in the marginal cost of driving if they have greater discretionary fuel use; on the other hand the disutility of price falls with income so they may be less likely to respond. In addition, low-income households may live far from public transportation, which would also hinder their ability to respond.

Using a census category measure of gross annual income provided directly by households in the recruitment survey, we show that low-income households indeed live further from the downtown and further from public transit. Our measure of household income includes pensions and government transfers. We define low income as below 65,000 AUD, or 51,636 USD.[13]

Table VII presents summary statistics by income. Half of our sample of low-income households are over the age of 65. The elderly spend less time driving, drive shorter distances, drive less at peak, and are less likely to drive into the center of town. Across all low-income households, although vehicles are indeed older, vehicle footprint is on average smaller, so average fuel efficiency is only slightly worse.

Low income households also make up a relatively small share of the drivers in the congested downtown area. Table B.4 shows that low income groups make up 30% of the household weekdays in our sample, but only 15% of the cordon entries.

We then look at how much drivers pay under the current system of fuel taxes plus vehicle registration fees, which are 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 VIII presents our results. We find that the low-income households would benefit from any form of road pricing that replaced 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.

We then use the road use experiment to estimate the price elasticity of road use separately for each income group. Table B.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 B.6 shows the price elasticity of low income households broken down by age and employment status. 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.

[13]This equates to the 40th percentile of gross income in Australia. 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.

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 IX 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]

Another potential source of disadvantage is limited access to public transit infrastructure. Using data on all rail and tram stations obtained from Public Transport Victoria (PTV), we break down daily distance traveled during baseline periods as a function of the distance of each household's SA1 to the CBD and the closest public transit station (Table X Panel (a)). As expected, baseline driving distances increase both with distance to public transit and distance to the CBD. Looking at the gradients across the table, we note that living within a kilometer of public transit is equivalent to living approximately 10 kilometers closer to the CBD when it comes to baseline driving.

In Table B.7 in the Appendix we summarize the treatment effects by distance to public transport. For the distance-based charge, we show in Table X Panel (b) that the largest reduction comes from among households that live close to the CBD and close to public transit (the two distances have a high correlation of $\rho = 0.68$) or far from both. 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 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

[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.

almost half of our sample is observed parking at or getting dropped off at a train station, we show in Table B.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 B.7 and Table VI. 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. Across all treatments, although we find responsiveness across income levels, the most responsive low-income households are also those that live within one kilometer of a train or tram station.

5.5 How we control for sub-treatment selection

In this section we explain our empirical approach to address sub-treatment selection into the distance-based charge. 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 II 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 B.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 B.6 and B.7 in the Appendix show good overlap in the propensity scores between treatment and control households with no extremely high or low values.

6 Robustness

In this section we 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 Substitution to unmonitored vehicles

Some households had the option of switching to unmonitored non-primary vehicles. Table B.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.

[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.

6.2 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 B.8 Panel (a) shows that most households maintain a positive travel account balance in the first 19, 24, or 27 days of the month, representing 90%, 80%, and 70% of all households, respectively. Figure B.8 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.

6.3 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 B.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 B.12 we check the balances of those who attrit and find no evidence that attritors were being paid less. Figure B.9 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

The Bureau of Infrastructure, Transport and Regional Economics (2015) estimate that the 'avoidable' social cost of traffic congestion in large Australian cities is over AU$16 billion per year. This number is made up of $6 billion in private time costs, $8 billion in business time costs, $1.5 billion in extra vehicle operating costs and $1 billion in extra air pollution costs. Congestion is clearly a massive and growing problem for cities around the world.

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.

Economists appear to agree on the potential benefits of congestion pricing. Grattan Institute (2017) argue that governments should offset existing annual registration fees, with network-wide time-of-day congestion charges. With residential electricity pricing, much of the efficiency gains from reduced congestion can be obtained from simple time-of-day or critical peak prices (Fowlie et al. (2017)). Can simple road use charges deliver similar efficiency gains? How closely do these road use charges need to track road conditions to capture the efficiency gains?

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 reduce 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 fairer way to charge for roads.

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A Tables

Table I: 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	344	0.037	1017	0.075	668
	[1.40]		(0.085)		(0.091)	
Has Children (=1)	0.36	343	0.024	1015	0.031	668
			(0.030)		(0.032)	
Distance home SA1 to CBD (km)	23.9	352	-0.43	1025	-1.17	673
	[16.6]		(0.97)		(1.01)	
Distance home SA1 to rail/tram (km)	3.72	352	-0.69**	1025	-1.03***	673
	[6.80]		(0.35)		(0.36)	
Vehicle						
Multiple Cars (=1)	0.50	347	0.0064	1024	0.016	673
			(0.031)		(0.033)	
Petrol (=1)	0.83	357	0.0014	1026	-0.0028	673
			(0.023)		(0.025)	
Average litres fuel per 100km	8.78	345	-0.033	1024	0.036	673
	[2.32]		(0.14)		(0.15)	
Visible GPS (=1)	0.27	357	-0.014	1026	-0.017	673
			(0.027)		(0.029)	
Trip						
Distance traveled (km/day)	33.4	357	0.61	1026	0.34	673
	[27.5]		(1.42)		(1.53)	
Trips taken (/day)	3.30	357	0.14	1026	0.077	673
	[1.89]		(0.10)		(0.11)	
Distance per trip (km/trip)	10.2	357	0.053	1026	0.16	673
	[5.37]		(0.31)		(0.33)	
Trip duration (min/trip)	22.2	357	-0.84	1026	-0.75	673
	[15.0]		(0.76)		(0.81)	
Average speed (km/hour)	25.8	357	0.48	1026	0.45	673
	[8.35]		(0.47)		(0.50)	
Time spent traveling (min/day)	67.3	357	1.67	1026	1.07	673
	[43.5]		(2.29)		(2.52)	
Time traveling at peak (min/day)	18.6	357	-0.085	1026	-0.54	673
	[13.8]		(0.79)		(0.84)	
Share of time spent driving at peak (%)	27.1	357	-1.03	1026	-1.33*	673
	[12.2]		(0.72)		(0.76)	
Share of hh-days entering CBD cordon (%)	3.80	357	0.0057	1026	-0.14	673
	[9.66]		(0.57)		(0.60)	
Share of households ever commuting (%)	42.3	357	-1.26	1026	-0.098	673
	[49.5]		(3.03)		(3.24)	
Average duration of commutes (min/day)	74.5	151	-0.49	421	-3.25	284
	[53.3]		(4.54)		(4.87)	

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 II: 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	344	0.10	352	-0.096	338	0.10	327	0.083	342	0.066	326
	[1.40]		(0.11)		(0.10)		(0.11)		(0.11)		(0.11)	
Has Children (=1)	0.36	343	0.055	348	-0.014	337	0.029	330	0.026	343	0.035	325
			(0.037)		(0.037)		(0.037)		(0.037)		(0.037)	
Distance home SA1 to CBD (km)	23.9	352	-1.60	354	2.96**	340	-2.66**	331	-1.71	344	-0.62	329
	[16.6]		(1.18)		(1.26)		(1.18)		(1.19)		(1.20)	
Distance home SA1 to rail/tram (km)	3.72	352	-1.17***	354	0.41	340	-1.30***	331	-1.12**	344	-0.94**	329
	[6.80]		(0.43)		(0.50)		(0.44)		(0.44)		(0.45)	
Vehicle												
Multiple Cars (=1)	0.50	347	0.0028	353	0.028	340	-0.012	331	0.010	344	0.021	329
			(0.038)		(0.038)		(0.038)		(0.038)		(0.039)	
Petrol (=1)	0.83	357	0.024	354	-0.032	340	0.011	332	-0.021	344	0.016	329
			(0.027)		(0.029)		(0.028)		(0.029)		(0.028)	
Average litres fuel per 100km	8.78	345	0.098	354	-0.13	339	-0.073	331	-0.041	344	0.12	329
	[2.32]		(0.18)		(0.18)		(0.17)		(0.17)		(0.18)	
Visible GPS (=1)	0.27	357	-0.040	354	0.011	340	-0.012	332	-0.022	344	-0.013	329
			(0.033)		(0.034)		(0.034)		(0.033)		(0.034)	
Trip												
Distance traveled (km/day)	33.4	357	0.45	354	4.13**	340	-2.83	332	0.92	344	-0.27	329
	[27.5]		(1.82)		(1.95)		(1.82)		(1.89)		(1.84)	
Trips taken (/day)	3.30	357	0.26**	354	0.039	340	0.13	332	0.096	344	0.058	329
	[1.89]		(0.13)		(0.13)		(0.14)		(0.13)		(0.13)	
Distance per trip (km/trip)	10.2	357	-0.46	354	1.68***	340	-1.07***	332	0.21	344	0.12	329
	[5.37]		(0.36)		(0.43)		(0.37)		(0.38)		(0.41)	
Trip duration (min/trip)	22.2	357	-1.84**	354	1.20	340	-1.85**	332	-0.64	344	-0.87	329
	[15.0]		(0.91)		(1.16)		(0.93)		(1.04)		(0.94)	
Average speed (km/hour)	25.8	357	-0.063	354	2.48***	340	-1.00*	332	0.51	344	0.39	329
	[8.35]		(0.56)		(0.64)		(0.57)		(0.59)		(0.60)	
Time spent traveling (min/day)	67.3	357	2.35	354	3.96	340	-1.41	332	1.66	344	0.46	329
	[43.5]		(2.90)		(3.13)		(2.94)		(3.12)		(2.92)	
Time traveling at peak (min/day)	18.6	357	-0.48	354	1.18	340	-0.95	332	-0.47	344	-0.62	329
	[13.8]		(0.96)		(1.05)		(0.97)		(0.98)		(1.00)	
Share of time spent driving at peak (%)	27.1	357	-1.54*	354	-0.46	340	-1.07	332	-1.17	344	-1.49*	329
	[12.2]		(0.88)		(0.93)		(0.88)		(0.88)		(0.91)	
Share of hh-days entering CBD cordon (%)	3.80	357	-0.30	354	0.91	340	-0.60	332	0.21	344	-0.49	329
	[9.66]		(0.68)		(0.79)		(0.65)		(0.72)		(0.69)	
Share of households ever commuting (%)	42.3	357	-3.88	354	-1.41	340	1.68	332	-3.34	344	3.30	329
	[49.5]		(3.68)		(3.74)		(3.78)		(3.71)		(3.80)	
Average duration of commutes (min/day)	74.5	151	-4.01	136	9.02	139	-6.26	146	-0.26	134	-5.92	150
	[53.3]		(5.92)		(6.00)		(5.57)		(5.77)		(5.83)	

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 III: Daily treatment effects under the distance charge

Panel (a): Daily treatment effects

VARIABLES	(1) Trips (/day)	(2) Distance (km/day)	(3) Duration (min/day)
Treatment = 10c per km	-0.120	-2.488**	-4.240***
	(0.0755)	(1.135)	(1.634)
Observations	148,069	148,069	148,069
R-squared	0.0304	0.00526	0.0126
Treated hh	353	353	353
Control hh	356	356	356
Mean dep var	3.394	32.75	67.30

Panel (b): Elasticity of travel demand

VARIABLES	(1) Overall	(2) Peak	(3) Off-peak
log per kilometer cost of travel	-0.1305***	0.0026	-0.1193**
	(0.048)	(0.057)	(0.048)
Observations	19,751	18,007	19,692
R-squared	0.0258	0.0119	0.0227
Treated hh	353	353	353
Control hh	344	344	344
CDW F-test	10574	10189	10559

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	-1.014*	-3.168***	-2.424	-1.219	-0.0931	-4.147***	-0.360***	-0.314	-3.567**
	(0.577)	(1.196)	(1.992)	(1.834)	(0.419)	(1.591)	(0.130)	(0.214)	(1.516)
Observations	148,069	148,069	76,150	47,441	148,069	148,069	148,069	148,069	148,069
R-squared	0.201	0.00703	0.00784	0.0112	0.0262	0.00859	0.00337	0.00538	0.0116
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	18.86	43.50	93.46	60.13	4.911	62.39	1.357	3.627	62.32

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. All regressions include household fixed effects. Panels (a) and (c) include date fixed effects; 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 dependant 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 IV: Daily treatment effects under the time-of-day charge

Panel (a): Daily treatment effects

VARIABLES	(1) Trips (/day)	(2) Distance (km/day)	(3) Duration (min/day)
Treatment = 15c peak 8c off-peak	-0.270***	-1.642	-3.199
	(0.0974)	(1.430)	(2.961)
Observations	139,396	139,396	139,396
R-squared	0.0292	0.00412	0.0113
Treated hh	344	344	344
Control hh	359	359	359
Mean dep var	3.369	33.69	68.49

Panel (b): Elasticity of travel demand

VARIABLES	(1) Overall	(2) Peak	(3) Off-peak
log per kilometer cost of travel	-0.0763	-0.0882	-0.0278
	(0.064)	(0.058)	(0.078)
Observations	18,424	16,799	18,370
R-squared	0.0295	0.0114	0.0242
Treated hh	344	344	344
Control hh	345	345	345
CDW F-test	8982	11729	9242

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	-1.902**	-1.280	-0.517	0.969	-0.167	-3.032	-0.443	-0.463	-2.294
	(0.797)	(2.417)	(2.466)	(3.566)	(0.664)	(2.937)	(0.270)	(0.323)	(2.763)
Observations	139,396	139,396	71,875	43,952	139,396	139,396	139,396	139,396	139,396
R-squared	0.199	0.00568	0.00761	0.00938	0.0284	0.00751	0.00357	0.00560	0.0105
Treated hh	344	344	344	344	344	344	344	344	344
Control hh	359	359	359	359	359	359	359	359	359
Mean dep var	19.17	44.41	96.12	60.59	5.116	63.37	1.670	3.951	62.87

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. All regressions include household fixed effects. Panels (a) and (c) include date fixed effects; panel (b) includes week fixed effects. Standard errors are clustered at the household level. hh = households. The bottom row shows the mean of the dependant 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 V: Daily treatment effects under the 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	-0.350***	-2.511*	-6.496***
	(0.100)	(1.454)	(2.416)
Observations	136,764	136,764	136,764
R-squared	0.0297	0.00447	0.0117
Treated hh	329	329	329
Control hh	359	359	359
Mean dep var	3.361	33.41	68.26

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	-1.353	-5.039***	0.184	-4.685*	-0.419	-6.077**	-0.566**	-0.272	-5.658**
	(0.839)	(1.805)	(2.631)	(2.716)	(0.765)	(2.361)	(0.275)	(0.315)	(2.233)
Observations	136,764	136,764	70,298	43,096	136,764	136,764	136,764	136,764	136,764
R-squared	0.199	0.00616	0.00769	0.00962	0.0262	0.00778	0.00337	0.00525	0.0109
Treated hh	329	329	329	329	329	329	329	329	329
Control hh	359	359	359	359	359	359	359	359	359
Mean dep var	19.14	44.23	95.42	60.71	5.100	63.16	1.581	3.729	62.95

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	-0.0988	-0.0552	0.352	-0.0401	-0.0732	-0.122**
	(0.166)	(0.154)	(0.300)	(0.0493)	(0.0511)	(0.0474)
Observations	33,554	33,554	33,554	66,565	66,565	66,565
R-squared	0.0215	0.00960	0.0121	0.0275	0.00957	0.0283
Treated hh	164	164	164	171	171	171
Control hh	154	154	154	161	161	161
Mean dep var	0.797	1.089	2.477	0.254	0.106	0.158

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 1. 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 include household and date fixed effects. Standard errors are clustered at the household level. hh = households. The bottom row shows the mean of the dependant 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 VI: Cordon entry by distance to CBD and public transit

Panel (a): Baseline cordon entry

Distance to CBD	Distance to public transit				
	0 to 0.5 km	0.5 to 1 km	1 to 1.5 km	1.5 to 3.5 km	3.5 to 34 km
0 to 11 km	0.086	0.093	0.085	0.067	
11 to 16 km	0.024	0.049	0.029	0.021	0.024
16 to 23 km	0.003	0.015	0.024	0.054	0.044
23 to 35 km	0.011	0.007	0.016	0.033	0.018
35 to 64 km		0.034	0.011	0.024	0.009

Panel (b): Cordon entry under distance plus cordon charge

Distance to CBD	Distance to public transit				
	0 to 0.5 km	0.5 to 1 km	1 to 1.5 km	1.5 to 3.5 km	3.5 to 34 km
1 to 11 km	0.019	-0.066**	0.052***	0.064***	
	(0.024)	(0.031)	(0.005)	(0.005)	
11 to 16 km	0.001	-0.048	0.070	0.020	
	(0.014)	(0.036)	(0.043)	(0.019)	
16 to 23 km	0.119***	-0.016**	-0.011	-0.001	0.015***
	(0.005)	(0.007)	(0.013)	(0.013)	(0.005)
23 to 35 km	0.009	-0.027***	-0.028*	-0.005	-0.028
	(0.011)	(0.006)	(0.016)	(0.019)	(0.045)
35 to 64 km		-0.117**	-0.000	-0.013	-0.019
		(0.054)	(0.012)	(0.011)	(0.028)

Notes: Panel (a) shows average daily cordon entry for households living at the given distances from the CBD and public transport. Home location proxied by center of corresponding SA1. Public transit includes train and tram. Distances to CBD and public transit reflect quintiles. The furthest off-diagonals have the fewest observations because of the positive correlation ($\rho = 0.68$) between distance to CBD and distance to public transit. Panel (b) shows coefficients on interaction between treatment and each quintile of distance between home SA1 and work and each quintile of distance between home SA1 and closest rail or tram station, on daily cordon entry, in a single regression. Dependent variable is indicator variable that takes a value of 1 if a household entered cordon in a given day. Regression includes 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 VII: 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 $\geq$ 65	0.100	622	0.38***	423	0.058	533	0.19***	216
	[0.30]		(0.025)		[0.23]		(0.025)	
Employed	0.86	630	-0.35***	430	1	540	0	220
	[0.35]		(0.026)		[0]		(0)	
Distance home SA1 to CBD (km)	22.1	630	5.04***	429	22.0	540	4.17***	220
	[15.0]		(0.99)		[15.0]		(1.23)	
Distance home SA1 to rail (km)	2.81	630	1.49***	429	2.81	540	0.85**	220
	[4.51]		(0.35)		[4.60]		(0.41)	
Vehicle								
Average litres fuel per 100km	8.56	627	0.46***	427	8.51	539	0.52***	219
	[2.16]		(0.14)		[2.16]		(0.18)	
Model year	2009.4	627	-2.71***	427	2009.4	539	-2.37***	219
	[4.39]		(0.32)		[4.30]		(0.38)	
Multiple Cars (=1)	0.61	630	-0.27***	430	0.61	540	-0.26***	220
	[0.49]		(0.030)		[0.49]		(0.039)	
Trip								
Distance traveled (km/day)	36.5	630	-5.97***	430	37.9	540	-1.04	220
	[23.4]		(1.47)		[24.1]		(2.01)	
Trips taken (/day)	3.51	630	-0.23**	430	3.55	540	0.17	220
	[1.66]		(0.10)		[1.67]		(0.14)	
Distance per trip (km/trip)	10.8	630	-1.25***	430	11.1	540	-0.77*	220
	[5.07]		(0.31)		[5.16]		(0.41)	
Time spent traveling (min/day)	72.1	630	-8.65***	430	74.1	540	0.83	220
	[36.4]		(2.38)		[37.4]		(3.20)	
Share of time spent driving at peak (%)	28.3	630	-4.71***	430	29.1	540	-2.46**	220
	[12.0]		(0.72)		[12.4]		(0.97)	
Share of households ever commuting (%)	50.2	630	-23.2***	430	58.1	540	-5.88	220
	[50.0]		(2.99)		[49.4]		(3.97)	
Average speed (km/hour)	26.9	630	-1.16**	430	27.4	540	-0.61	220
	[7.77]		(0.48)		[7.88]		(0.62)	
Share of hh-days entering CBD cordon (%)	5.21	630	-3.28***	430	5.67	540	-3.08***	220
	[10.7]		(0.56)		[11.4]		(0.83)	
Distance inside cordon (km/day)	0.40	630	-0.17***	430	0.43	540	-0.079	220
	[0.82]		(0.057)		[0.87]		(0.085)	

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 VIII: Changes in bill assuming no price responsiveness

Annual income	Households	Weekly fuel tax (AUD)	Change in weekly expenditures under		
			Distance charge	TOD charge	Cordon charge
Less than $20,800	83	5.92	-4.18	-4.51	-3.32
			(75%)	(76%)	(77%)
$20,800 to $41,600	162	7.39	-3.05	-3.45	-3.21
			(67%)	(68%)	(71%)
$41,600 to $65,000	185	9.34	0.43	0.13	-0.47
			(60%)	(61%)	(63%)
$65,000 to $104,000	260	8.96	1.40	1.43	1.25
			(53%)	(54%)	(55%)
$104,000 to $156,000	203	9.56	2.36	2.57	2.18
			(49%)	(49%)	(49%)
$156,000 or more	167	8.09	0.16	0.65	1.29
			(58%)	(54%)	(52%)
Did not say	319	8.20	-0.55	-0.52	-0.50
			(58%)	(60%)	(62%)

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 IX: 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	-0.13	-12.44	2.74	-0.60	-10.34	3.90
20,800 to 41,600	162	-0.13	-13.81	1.93	-0.19	-13.47	2.18
41,600 to 65,000	185	-0.13	-16.53	-0.26	-0.18	-16.21	-0.02
65,000 to 104,000	260	-0.13	-17.26	-1.10	0.10	-18.97	-1.85
104,000 to 156,000	203	-0.13	-18.19	-1.84	-0.22	-17.55	-1.43
Greater than 156,000	167	-0.13	-16.24	-0.37	0.05	-17.46	-0.89
Did not say	319	-0.13	-15.76	0.18	-0.21	-15.25	0.52

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	-0.09	-0.03	-12.22	3.44	-0.32	-0.47	-10.62	4.26
20,800 to 41,600	162	-0.09	-0.03	-13.58	2.66	-0.17	-0.02	-13.41	2.84
41,600 to 65,000	185	-0.09	-0.03	-16.52	0.29	-0.31	0.03	-16.02	0.72
65,000 to 104,000	260	-0.09	-0.03	-17.46	-0.76	-0.04	0.08	-18.05	-0.98
104,000 to 156,000	203	-0.09	-0.03	-18.51	-1.62	-0.05	-0.22	-17.96	-1.37
Greater than 156,000	167	-0.09	-0.03	-16.68	-0.30	0.02	0.32	-18.34	-0.99
Did not say	319	-0.09	-0.03	-15.89	0.56	-0.01	-0.13	-15.84	0.57

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.

Table X: Daily distance traveled by distance to CBD and public transit

Panel (a): Baseline distance (kilometers/day)

Distance to CBD	Distance to public transit				
	0 to 0.5 km	0.5 to 1 km	1 to 1.5 km	1.5 to 3.5 km	3.5 to 34 km
0 to 11 km	27.6	30.5	37.7	36.0	33.8
11 to 16 km	28.9	31.8	29.2	39.8	36.2
16 to 23 km	32.1	36.8	39.8	35.1	31.8
23 to 35 km	31.3	35.1	43.5	39.2	48.6
35 to 64 km	44.3	53.2	51.1	56.2	65.7

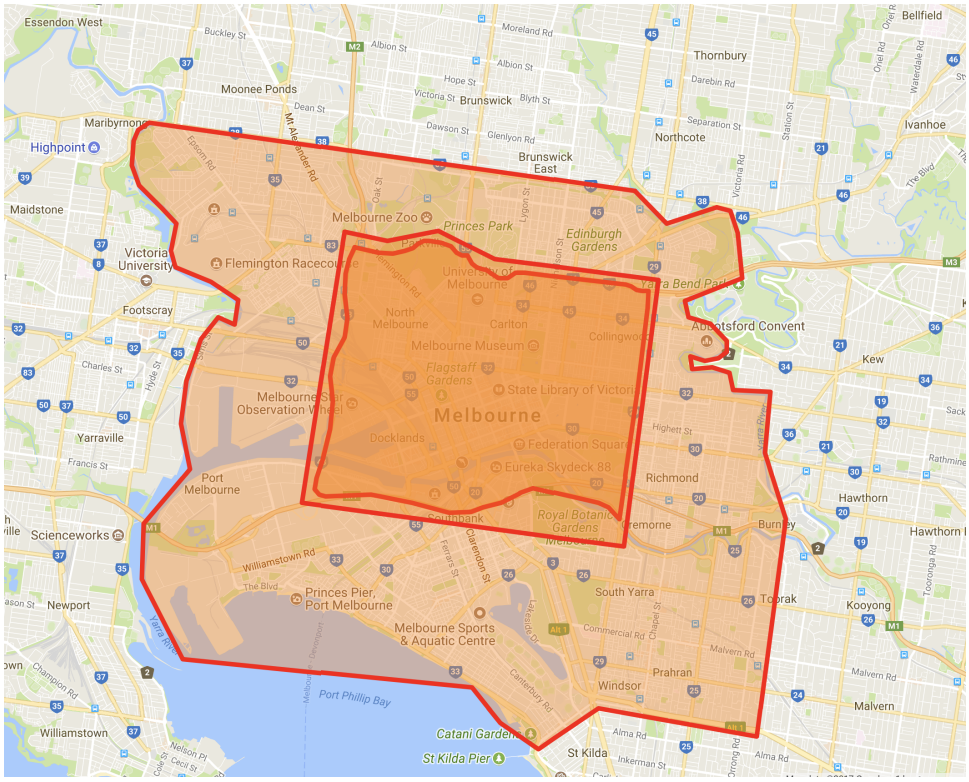
Panel (b): Distance (kilometers/day) under distance-based charge

Distance to CBD	Distance to public transit				
	0 to 0.5 km	0.5 to 1 km	1 to 1.5 km	1.5 to 3.5 km	3.5 to 34 km
0 to 11 km	-5.319***	-7.204	-6.080**	-12.454	
	(1.591)	(6.332)	(2.959)	(12.174)	
11 to 16 km	-3.882	2.331	2.019	-1.862	-8.461
	(4.897)	(2.464)	(1.982)	(3.921)	(6.543)
16 to 23 km	0.888	2.159	-0.704	-3.908*	0.296
	(2.039)	(3.467)	(2.334)	(2.103)	(5.287)
23 to 35 km	8.088	-3.291	-1.589	-2.459	-8.335*
	(5.418)	(2.553)	(3.616)	(6.431)	(4.918)
35 to 64 km	5.402*	0.994	7.652	-6.191	-6.482*
	(2.983)	(4.397)	(7.671)	(4.895)	(3.962)

Notes: Panel (a) shows average daily distance traveled (in kilometers/day) for households living at the given distances from the CBD and public transport. Home location proxied by center of corresponding SA1. Public transit includes train and tram. Distances to work and public transport reflect quintiles. The furthest off-diagonals have the fewest observations because of the positive correlation ($\rho = 0.68$) between distance to CBD and distance to public transit. Panel (b) shows coefficients on interaction between treatment and each quintile of distance between home SA1 and work and each quintile of distance between home SA1 and closest rail or tram station, on daily distance traveled, in a single regression. Regression includes household fixed effects and date fixed effects. Standard errors are clustered at the household level. Regression includes inverse probability weights to address sub-treatment selection. *** p<0.01, ** p<0.05, * p<0.1.

B Figures

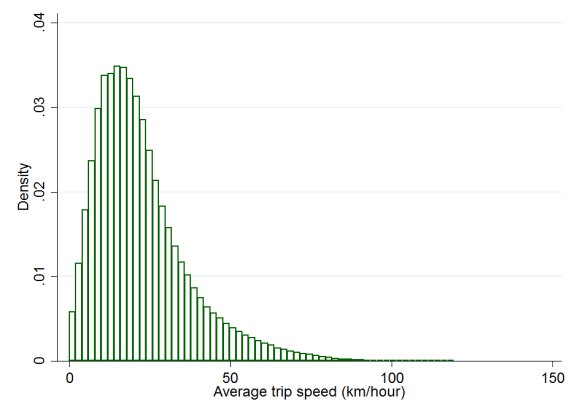
Figure 1: Cordon area



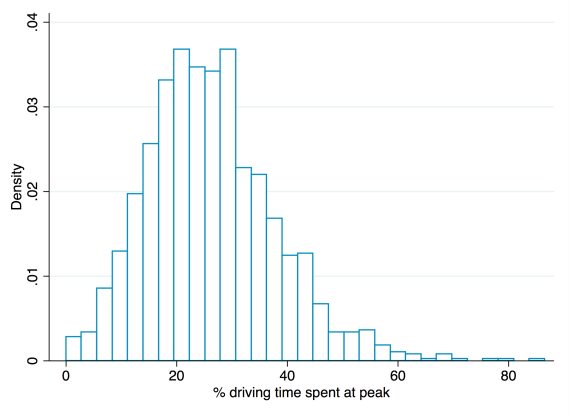
Notes: The cordon charge applied to any day in which a driver entered the inner cordon (dark shade) at a priced time. This region is bounded by Alexandra Parade and Elliott Avenue to the North, CityLink to the West and South, and Hoddle Street to the East. Note that travel along these boundary roads 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 2: Distribution of key variables

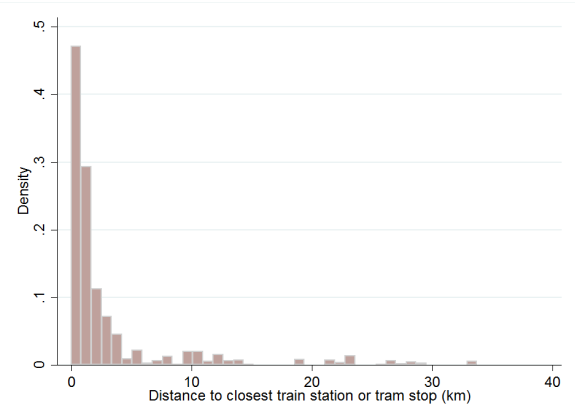
(a) Average trip speed



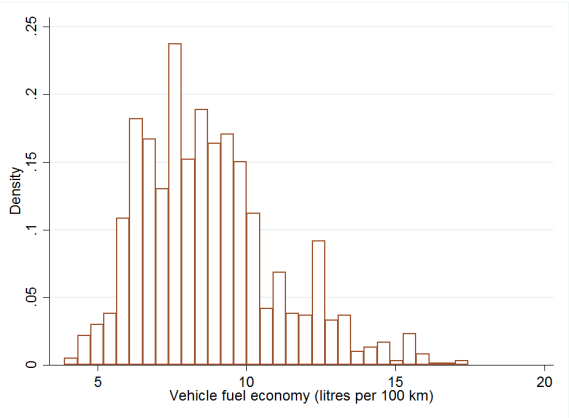
(b) Time driving at peak



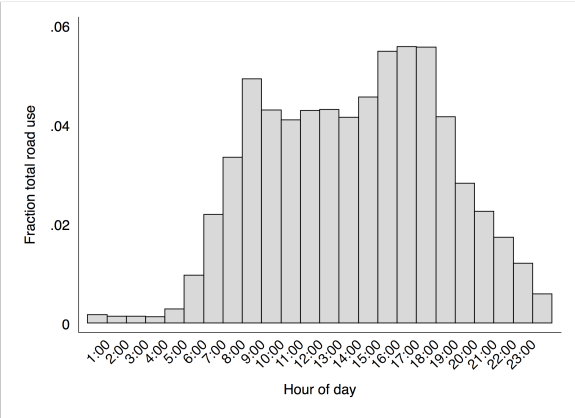
(c) Distance to closest commuter rail or tram station



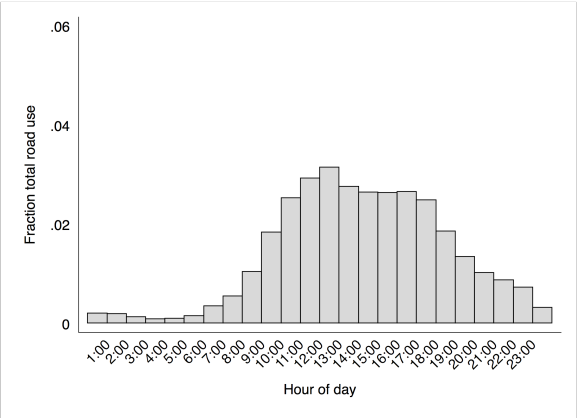
(d) Vehicle fuel economy



(e) Distance by hour of day, weekday



(f) Distance by hour of day, weekend



Notes: Panel (a): average speed per trip taken (total trip distance divided by total trip duration) in kilometers per hour. Panel (b): percentage of the time a household spends driving at peak times (Monday-Friday 7-9am and 3-6pm) during the baseline period. Panel (c): distance in kilometers between home SA1 and closest train station or tram stop. Panel (d) Fuel economy in liters per 100 kilometers of household's primary, monitored vehicle. Panels (e) and (f): kilometers traveled by all households by hour of day and weekday/weekend during baseline period.

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

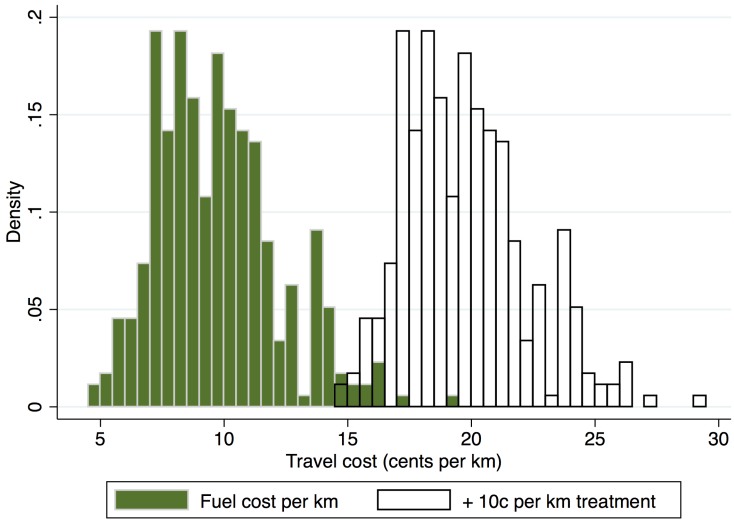


Figure 4: Effect of distance-based charge on daily distance traveled, by time of day

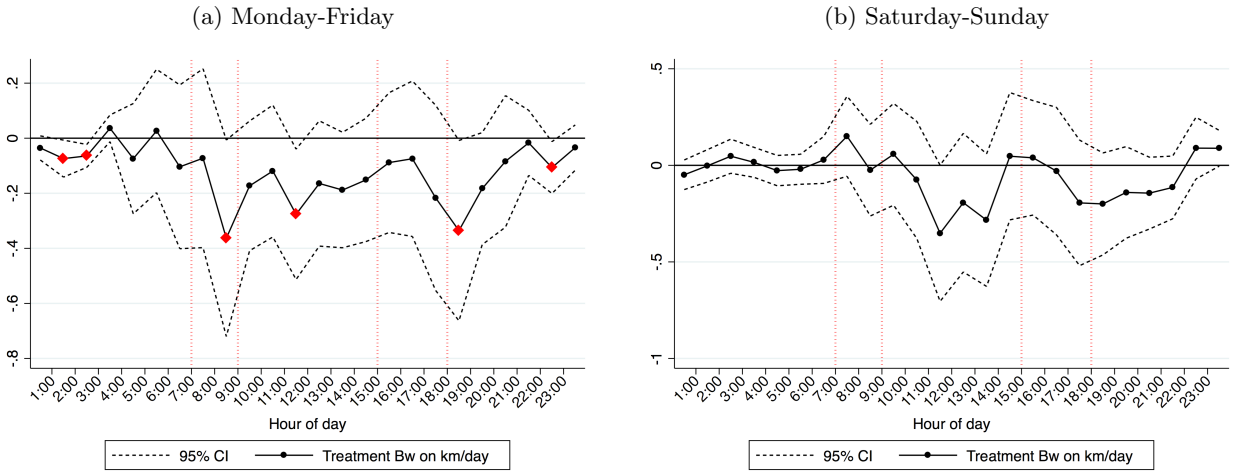
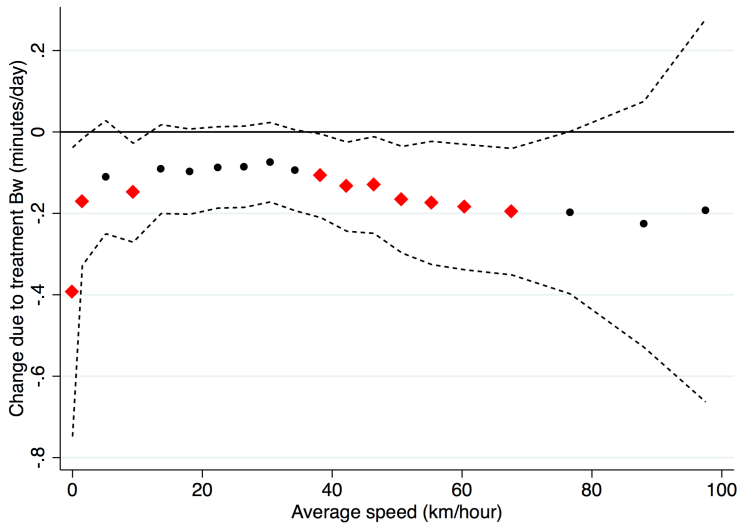


Figure 5: Effect of distance-based charge on minutes traveled at different speeds



Notes: Distance-based charge is 10c per kilometer. Red diamonds indicate estimates that are significant at the 5% significance level. Black dashed lines are 95% confidence intervals.

Figure 6: Effect of time-of-day distance-based charge on daily distance traveled, by time of day

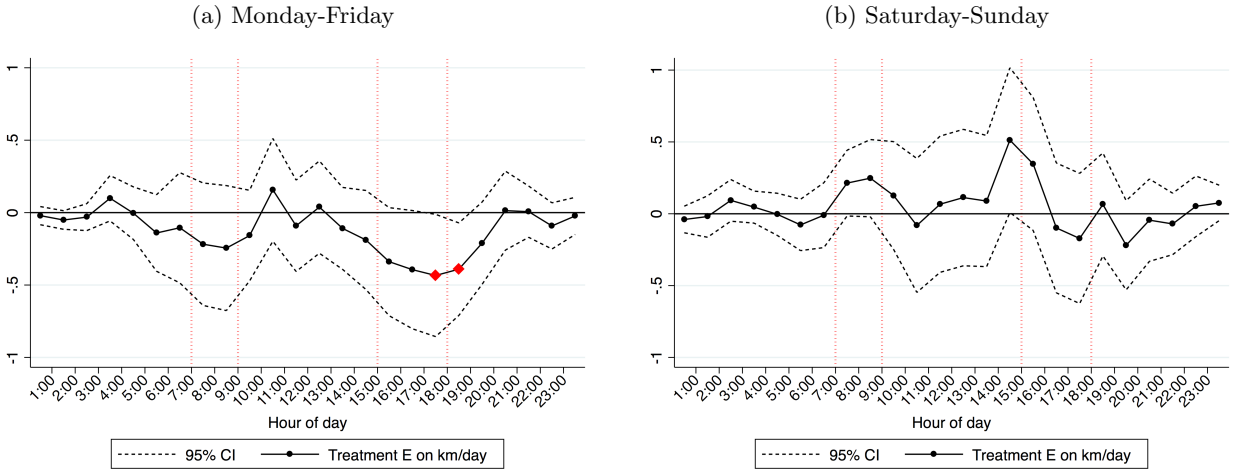
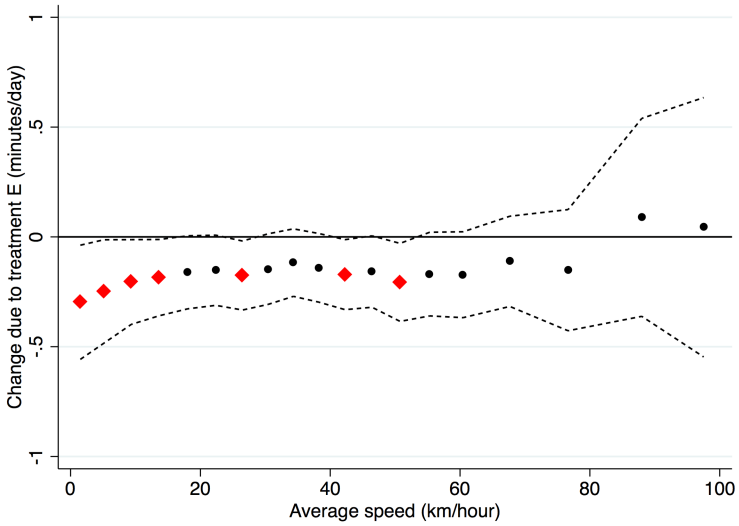


Figure 7: Effect of time-of-day distance-based charge on minutes traveled at different speeds



Notes: Time-of-day charge is 15c per kilometer peak, 8c per kilometer off-peak. Peak is 7-9am and 3-6pm Monday-Friday. Red diamonds indicate estimates that are significant at the 5% significance level. Black dashed lines are 95% confidence intervals.

Figure 8: Effect of distance and cordon charge on daily distance traveled, by time of day

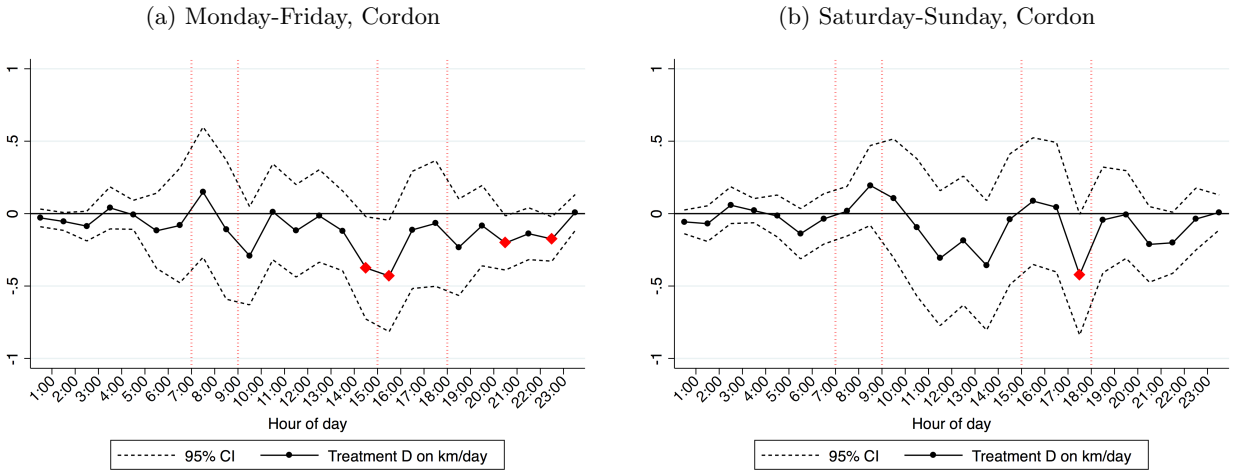
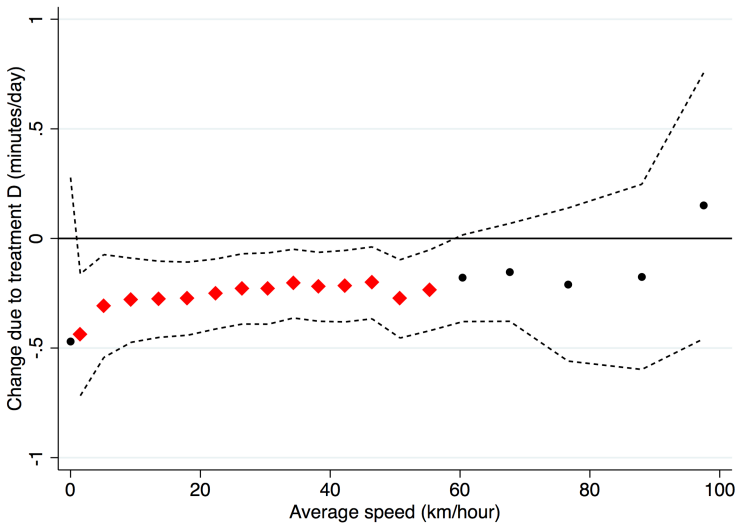
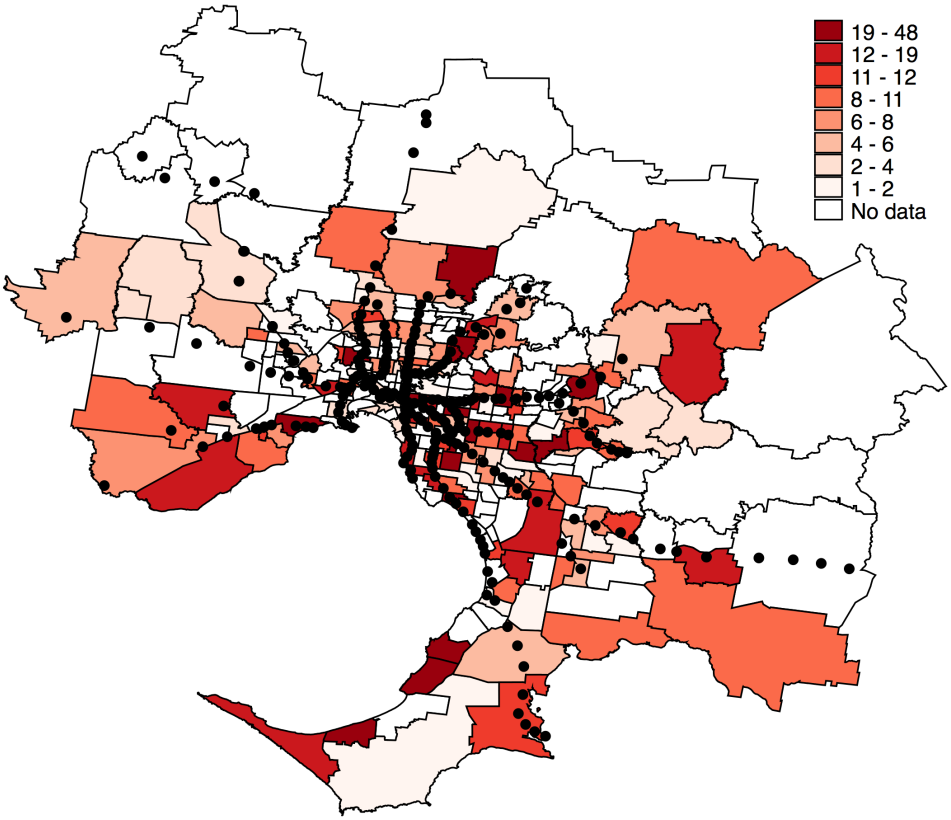


Figure 9: Effect of distance and cordon charge on minutes traveled at different speeds



Notes: Distance plus cordon charge is 8c per kilometer plus $8 per day for cordon entry. Red diamonds indicate estimates that are significant at the 5% significance level. Black dashed lines are 95% confidence intervals.

Figure 10: Geographical distribution of households and rail stations



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.

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Table B.1: Unweighted daily average treatment effects

VARIABLES	(1) Trips (/day)	(2) Distance (km/day)	(3) Duration (min/day)
Treatment = 10c per km	-0.173**	-2.615**	-5.032***
	(0.0773)	(1.076)	(1.656)
Observations	148,689	148,689	148,689
R-squared	0.0288	0.00455	0.0113
Treated hh	354	354	354
Control hh	359	359	359
Mean dep var	3.421	33.43	68.65

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 B.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	-2.488**	-1.236	-0.0394***	0.0323	0.276
	(1.135)	(1.180)	(0.0123)	(0.0485)	(0.920)
Observations	148,069	108,362	148,069	108,362	106,231
R-squared	0.00526	0.00844	0.0214	0.0225	0.00944
Treated hh	353	353	353	353	353
Control hh	356	356	356	356	356
Mean dep var	32.75	44.81	0.731	3.251	26.40

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 in that day. 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.

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

Table B.3: Top 25 congested roads

VARIABLES	(1) Local	(2) Express	(3) Local	(4) Express	(5) Local	(6) Express
Treatment = 10c per km	-0.102	-0.0474				
	(0.0906)	(0.194)				
Treatment = 15c peak 8c off-peak			-0.178*	-0.152		
			(0.102)	(0.185)		
Treatment = 8c per km and cordon					-0.223**	-0.0235
					(0.106)	(0.198)
Observations	126,984	126,984	139,396	139,396	136,764	136,764
R-squared	0.00476	0.00349	0.00400	0.00280	0.00522	0.00288
Treated hh	353	353	344	344	329	329
Control hh	356	356	359	359	359	359
Mean dep var	1.476	1.946	1.489	2.120	1.488	2.082

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

VARIABLES	(1) Local	(2) Express	(3) Local	(4) Express	(5) Local	(6) Express
Treatment = 10c per km	-0.144	-0.0229				
	(0.191)	(0.162)				
Treatment = 15c peak 8c off-peak			-0.360*	-0.114		
			(0.216)	(0.153)		
Treatment = 8c per km and cordon					-0.427**	-0.0333
					(0.216)	(0.167)
Observations	126,984	126,984	139,396	139,396	136,764	136,764
R-squared	0.00607	0.00354	0.00733	0.00298	0.00840	0.00334
Treated hh	353	353	344	344	329	329
Control hh	356	356	359	359	359	359
Mean dep var	3.152	1.537	3.191	1.674	3.177	1.664

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 B.4: Baseline cordon entry by income

	HH weekdays	Cordon entries	% HH weekdays		% Cordon entries	
Less than 20,800	3433	179	5	5	4	4
20,800 to 41,600	7258	215	11	17	5	9
41,600 to 65,000	8343	312	13	30	7	15
65,000 to 104,000	12047	1067	19	49	23	39
104,000 to 156,000	9586	896	15	64	19	58
Greater than 156,000	7610	1002	12	76	22	80
Did not say	15613	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 B.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	-0.5656**	-0.1839	-0.1709	0.0943	-0.0802	-0.1993**
	(0.244)	(0.138)	(0.116)	(0.102)	(0.076)	(0.094)
Observations	1,131	2,235	2,757	3,649	5,222	4,757
R-squared	0.0768	0.0338	0.0766	0.0347	0.0337	0.0272
Treated hh	23	41	45	61	94	89
Control hh	20	36	52	69	89	78
CDW F-test	1193	1138	1356	1733	3513	2591

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 B.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	-0.3203**	-0.1688	-0.3587***	-0.1518	-0.3564***	-0.2099*
	(0.137)	(0.115)	(0.102)	(0.140)	(0.126)	(0.119)
Observations	3,076	3,011	3,338	2,785	2,168	3,922
R-squared	0.0721	0.0401	0.0817	0.0374	0.0718	0.0434
Treated hh	48	59	54	55	45	64
Control hh	60	48	59	49	37	70
CDW F-test	1668	1643	1873	1506	1401	1939

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

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

	(1)	(2)	(3)	(4)	(5)
	0 to	0.5 to	1 to	1.5 to	3.5 to
VARIABLES	0.5 km	1 km	1.5 km	3.5 km	34 km
Treatment = 10c per km	-4.469***	-0.265	1.779	-2.632	-6.621**
	(1.499)	(2.258)	(1.847)	(3.366)	(3.143)
Observations	29,866	29,893	27,790	33,137	26,407
R-squared	0.0153	0.0143	0.0155	0.0156	0.0196
Treated hh	76	76	68	75	58
Control hh	72	64	69	76	70
Mean dep var	26.95	29.84	27.99	38.74	40.21

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

	(1)	(2)	(3)	(4)	(5)
	0 to	0.5 to	1 to	1.5 to	3.5 to
VARIABLES	0.5 km	1 km	1.5 km	3.5 km	34 km
Treatment = 15c peak 8c off peak	0.293	-1.981**	-0.169	-1.908	-1.413
	(0.888)	(0.896)	(0.961)	(1.432)	(1.069)
Observations	28,147	28,141	24,294	31,892	25,809
R-squared	0.0794	0.0994	0.138	0.128	0.130
Treated hh	74	78	56	76	60
Control hh	72	64	69	77	70
Mean dep var	7.123	7.768	8.481	11.05	10.21

Panel (c): Cordon entry (/day)

	(1)	(2)	(3)	(4)	(5)
	0 to	0.5 to	1 to	1.5 to	3.5 to
VARIABLES	0.5 km	1 km	1.5 km	3.5 km	34 km
Treatment = 8c per km and cordon	0.0472	-0.116**	0.0859	-0.00148	-0.0709
	(0.0292)	(0.0474)	(0.0557)	(0.0224)	(0.0683)
Observations	8,979	6,396	5,476	8,255	4,387
R-squared	0.0271	0.0448	0.0447	0.0278	0.0433
Treated hh	46	31	31	37	19
Control hh	44	29	23	33	23
Mean dep var	0.166	0.178	0.121	0.103	0.0935

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 B.8: Driving to train stations

VARIABLES	(1)	(2)	(3)
Treatment = 10c per km	0.000471		
	(0.0102)		
Treatment = 15c peak 8c off-peak		-0.0109	
		(0.0153)	
Treatment = 8c per km and cordon			-0.0196
			(0.0140)
Observations	32,948	30,390	33,573
R-squared	0.0247	0.0166	0.0161
Treated hh	76	71	90
Control hh	76	78	78
Mean dep var	0.0607	0.0606	0.0565

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 B.9: Marginal effects from multinomial logit model

VARIABLES	(1) A	(2) B	(3) 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 B.10: Elasticity by number of cars parked overnight

	(1) Distance	(2)	(3) Time of Day	(4)
VARIABLES	Multicars	One car	Multicars	One car
log price	-0.0786	-0.1835***	0.0074	-0.1708*
	(0.066)	(0.070)	(0.090)	(0.092)
Observations	10,044	9,610	9,421	8,924
R-squared	0.0242	0.0345	0.0279	0.0387
Treated hh	178	174	176	168
Control hh	170	172	170	173
CDW F-test	4887	5893	4524	4468

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 B.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 B.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.

Figure B.1: Top 25 congested roads (Austroads 2016)

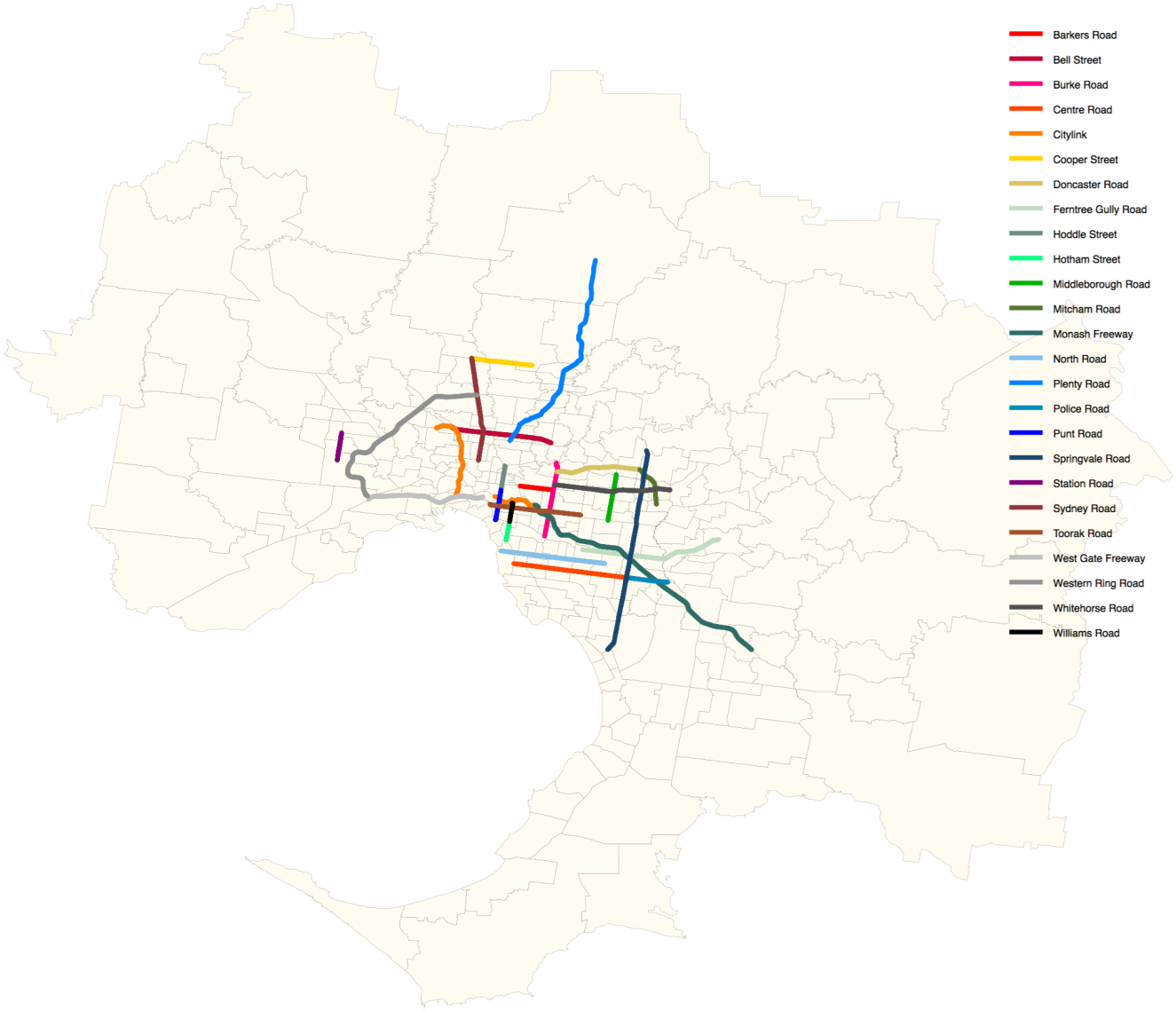
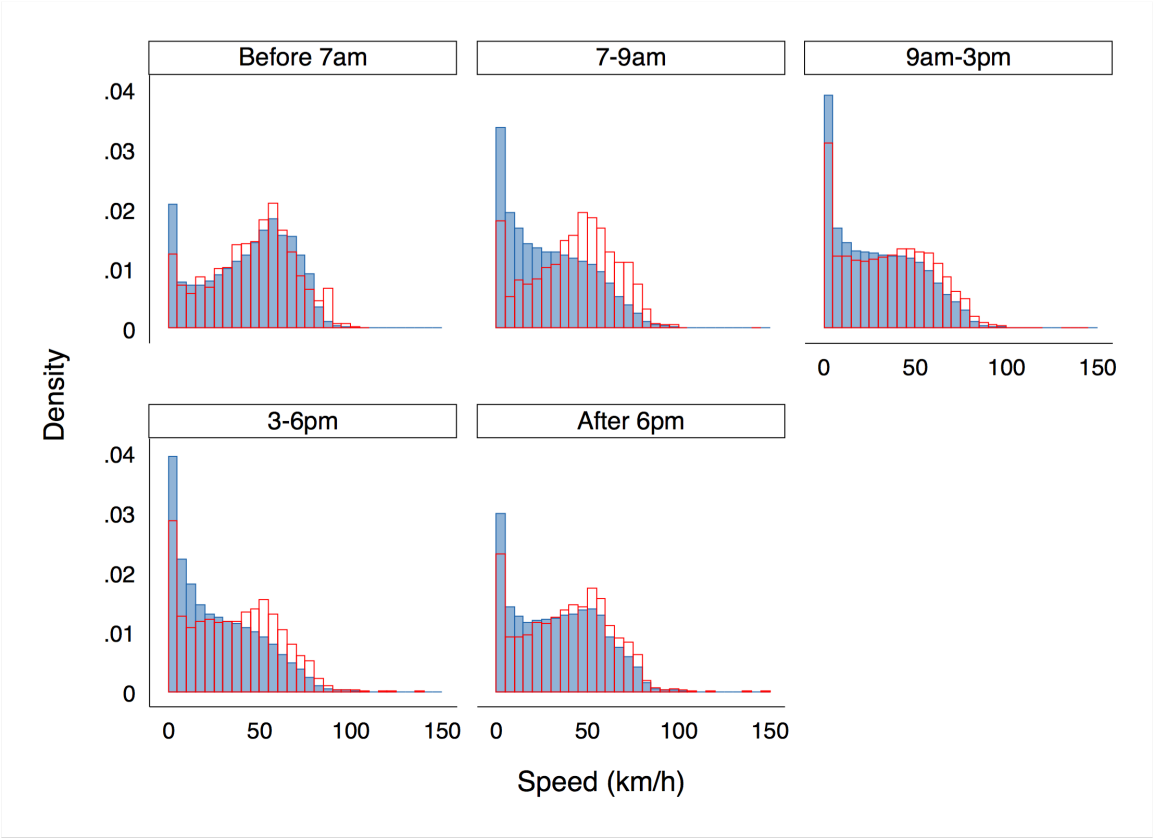


Figure B.2: Average speeds (km/hr) on local congested roads during baseline

	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	21.2	16.2	16.0	16.9	15.7	19.6	20.9	16.8	17.2	16.5
Cordon border	45.3	31.9	34.3	37.9	26.8	44.8	47.9	38.6	40.3	37.5
Outer cordon	40.6	26.6	26.9	31.5	25.3	41.0	37.1	29.6	34.3	31.3
Hotham Street	27.7	19.5	25.7	26.5	22.6	34.4	34.3	25.2	29.7	25.7
Punt Road	30.1	15.8	19.2	22.3	17.4	33.2	31.5	20.6	23.8	19.8
Williams Road	31.5	23.9	22.3	25.8	21.3	34.8	30.3	21.8	28.2	23.1
Station Road	32.0	26.0	33.4	35.1	27.5	43.0	52.5	31.5	31.9	32.6
Hoddle Street	32.0	18.0	20.6	23.1	17.3	30.0	30.4	21.3	24.6	21.0
Cooper Street	33.4	34.7	28.5	38.8	29.9	36.8	46.0	34.0	42.8	35.2
Ferntree Gully Road	34.0	33.9	36.5	41.6	34.7	52.3	45.3	39.5	46.7	41.7
Toorak Road	34.4	20.4	20.0	24.4	17.7	32.8	28.8	21.2	26.5	22.4
Police Road	34.9	22.1	23.3	29.6	22.8	35.9	32.6	24.0	33.7	28.1
Doncaster Road	35.1	27.5	25.1	27.7	25.2	38.0	31.1	26.3	31.0	26.2
Bell Street	36.2	30.6	29.1	36.6	26.2	42.6	42.3	30.7	38.5	32.8
Sydney Road	36.4	27.3	23.5	29.3	22.5	39.4	28.9	24.6	30.7	25.6
Middleborough Road	36.8	28.0	25.1	30.7	21.7	43.4	32.0	25.0	35.6	26.7
Burke Road	38.9	23.9	25.5	31.2	21.4	39.4	34.5	26.9	33.1	28.6
Centre Road	39.1	23.2	20.6	24.3	19.8	33.9	29.7	21.1	25.5	22.0
Barkers Road	39.2	18.7	25.1	25.7	21.0	40.3	29.4	25.7	31.3	26.1
Mitcham Road	40.9	33.6	35.1	35.4	34.2	48.2	37.6	36.7	41.4	38.9
Springvale Road	42.4	27.8	28.6	34.7	26.0	45.0	38.5	30.0	37.9	31.8
Whitehorse Road	42.6	29.1	25.4	32.7	25.6	44.4	34.3	28.0	36.3	31.6
North Road	45.4	27.5	29.6	29.8	24.5	42.1	34.6	29.3	32.7	30.0
Plenty Road	53.7	42.6	44.7	47.8	39.1	58.7	50.7	43.9	52.7	45.7

Figure B.3: Top 25 congested roads: observed speeds (blue = Monday-Friday, red=public holiday)

(a) Local roads



(b) Express roads

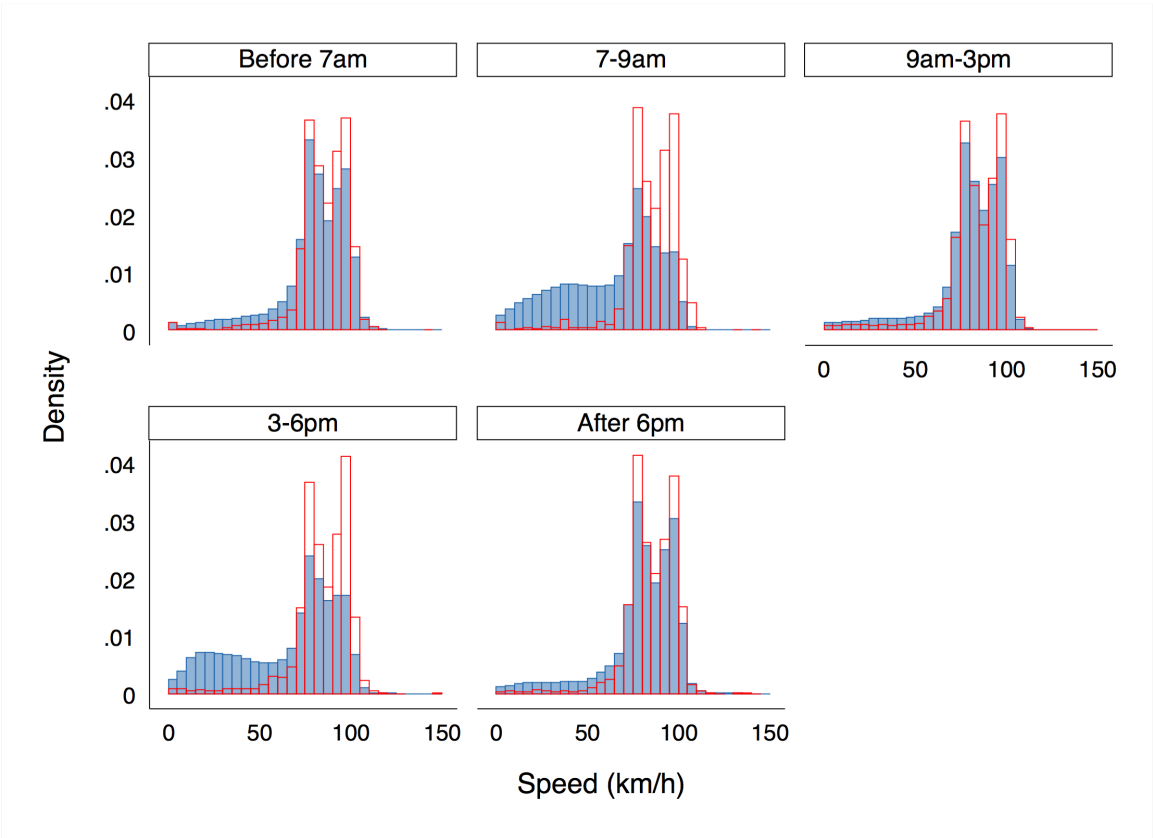
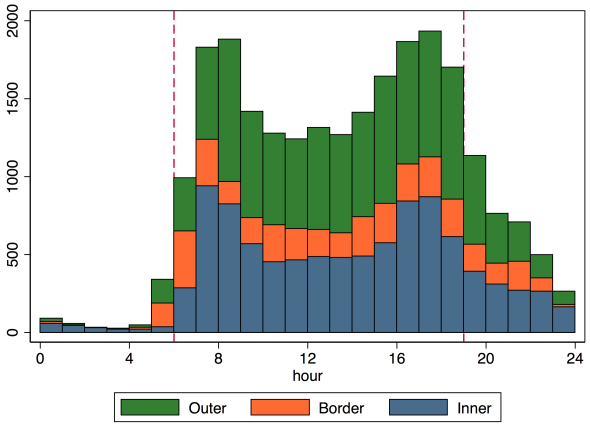
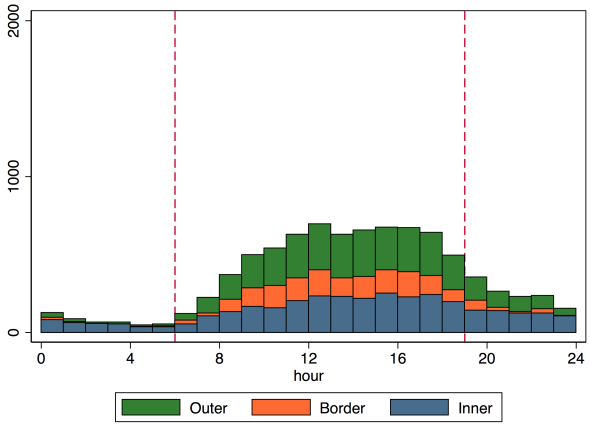


Figure B.4: Baseline cordon use: number of driver-days with trips into cordon

(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 B.5: Cordon entry by distance from CBD and public transport

(a) Baseline cordon entry by distance quantile

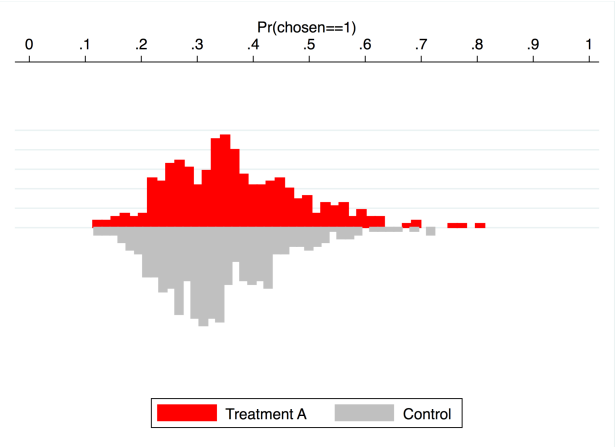
	Distance to public transit				
Distance to CBD	0 to 0.5 km	0.5 to 1 km	1 to 1.5 km	1.5 to 3.5 km	3.5 to 34 km
0 to 11 km	32.9%	9.1%	2.7%	1.1%	
11 to 16 km	1.7%	10.3%	4.1%	1.9%	0.4%
16 to 23 km	0.1%	1.4%	5.1%	8.7%	2.3%
23 to 35 km	0.4%	0.6%	1.4%	6.0%	2.7%
35 to 64 km		1.5%	0.7%	2.2%	2.8%

(b) Distribution of households by distance quantile

	Distance to public transit				
Distance to CBD	0 to 0.5 km	0.5 to 1 km	1 to 1.5 km	1.5 to 3.5 km	3.5 to 34 km
0 to 11 km	14.5%	3.7%	1.2%	0.6%	
11 to 16 km	2.8%	7.9%	5.4%	3.3%	0.6%
16 to 23 km	0.8%	3.3%	7.9%	6.0%	1.9%
23 to 35 km	1.3%	3.3%	3.3%	6.8%	5.6%
35 to 64 km	0.5%	1.7%	2.4%	3.4%	11.7%

Figure B.6: Overlap in propensity scores

(a) Treatment A



(b) Treatment B

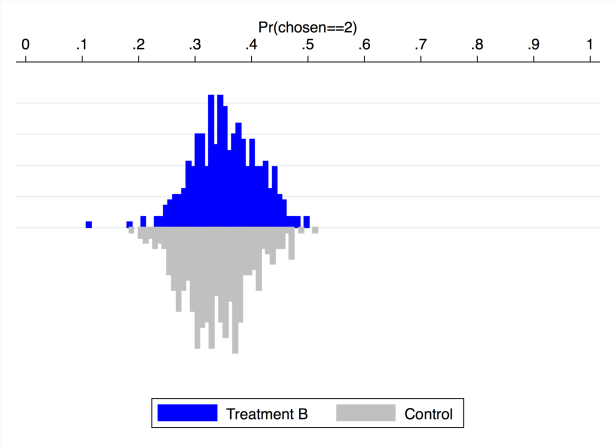
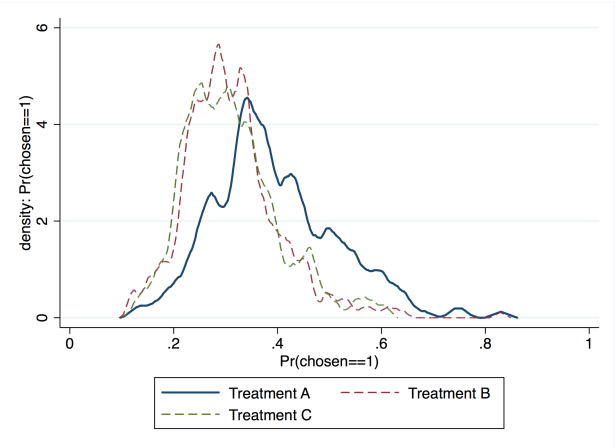


Figure B.7: Conditional densities for probability of treatment

(a) Treatment A



(b) Treatment B

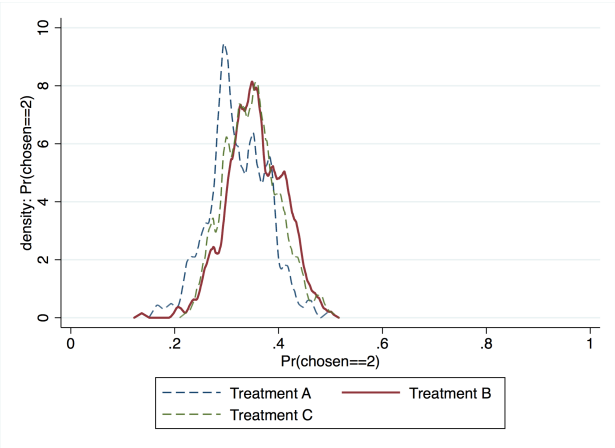
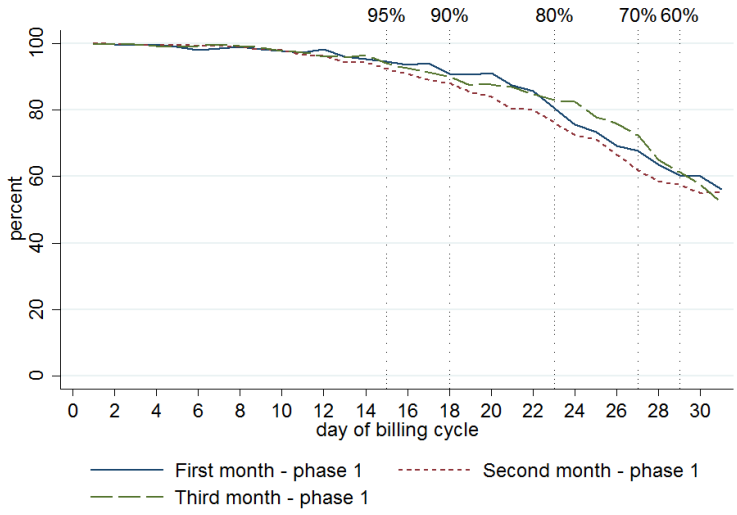


Figure B.8: No evidence of end-of-cycle reversal of driving reduction

(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

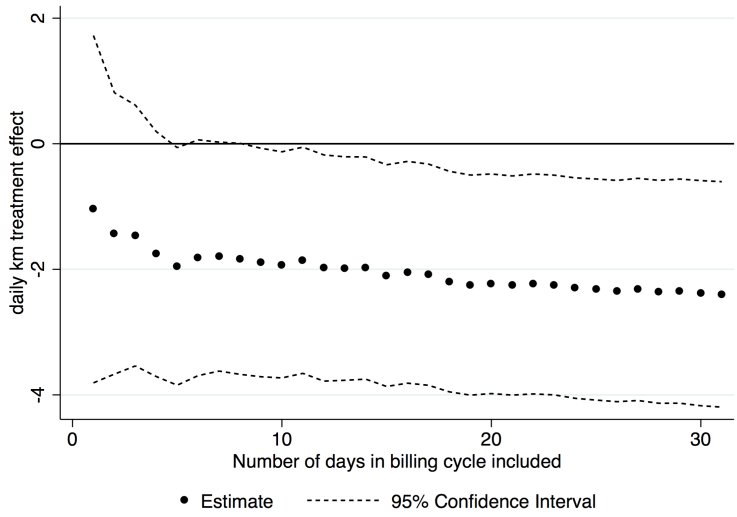
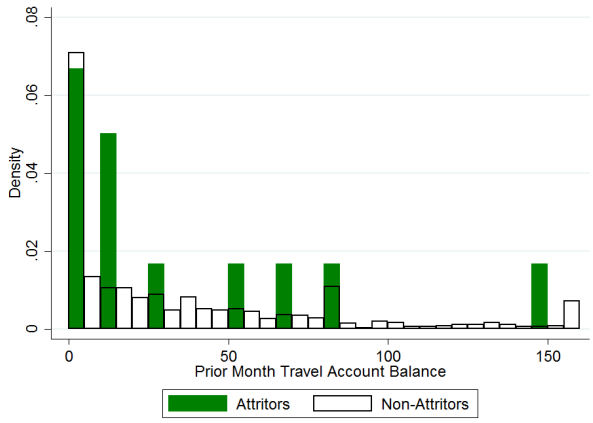


Figure B.9: Travel account balances in prior month

(a) Phase 1 - Treatment



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

