A Online Appendix for "Peak-Hour Road Congestion Pricing: Experimental Evidence and Equilibrium Implications"

Contents

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A.1 Smartphone App Data Collection

This section contains additional information about the smartphone app used to collect GPS trip data.

To conserve battery power, updates were collected at variable time intervals, between every 30 seconds while traveling and every 6 minutes, when in stationary mode. The phone location is identified by the phone operating system using GPS information, as well as cell phone network and WiFi information. (I will refer to this data simply as *GPS data.*) The app uploads data to a server at regular intervals using the phone's data or WiFi connection. The app has a simple interface that shows a map with the user's current location, and users could receive notifications in the phone notification panel.

The algorithm tags trips outside Bangalore, defined as more than 18km away from the city center.

The app sometimes did not collect GPS data, for either technical or human factors, if the phone or the location services are switched off, if app permissions are revoked, or if the phone is unable to determine its own location. I classify daily data into three quality categories based on the total duration without location data, and the total distance traveled without precise route information: good quality data, insufficient data, and no data. During the experiment, around 75% of days are good quality, which is the category used for analysis. I also define a measure of trip data quality, where good quality trips have precise departure and arrival times, are neither too short nor too long, do not have "jumps" without data, are not short loops, and are not very "swiggly." During the experiment, 64% of all non-weekend, non-holiday, daytime trips are good quality and thus included in the sample.[29]

[29] The largest category of low quality trips are due to imprecise departure time and short duration.

I identify home and common, recurring daytime destinations at the commuter level (such as a work or school) using a clustering algorithm to group locations into groups, followed by manual review of the location groups most frequently visited. Next, I compute the fraction of distance traveled between "home" and "work," as well as the fraction of days present at work. Using these two variables, I classify participants into regular and variable commuters.

A.2 Trip Classification Algorithm

This section describes the algorithm that processes raw GPS data obtained from the study smartphone app into trips. This algorithm was used to process 74,059 days of data, covering 22,434,466 unique locations points from 2,300 devices.

The algorithm has five main parts:

1. Remove outliers from raw data.
2. Segment each day into "trip" "location" segments, as well as "gap" and "jump" (missing data) segments.
3. Classify home and work locations for experiment participants. (This step was not used during the experiment, only for final data analysis.)
4. Combine segments into (final) locations and (final) trips.
5. Compute quality measures for each trip and for each day.

I now describe each part in more detail.

1. Removing GPS Data Outliers. Smartphones sometimes temporarily report an erroneous location, which the algorithm identifies and drops. The main cases are:

- *imprecise location.* When location is determined solely based on the cell phone tower, the accuracy is in the range of 600-800 meters. Points with accuracy radius above 400 meters are initially dropped.[30]
- *sharp angle jump.* This occurs when the location jumps to a precise but distant location, before returning to the current location. Such points are identified when a speed threshold is exceeded and the location returns close to the original location. These points are dropped.
- *multiple jumps.* This case occurs when several location jumps take place in succession. This case is identified similarly to the previous case. These points are dropped.
- *lazy location.* This occurs when the smartphone is moving continuously yet the location remains stuck for a period of time and then jumps suddenly. A point is labeled as "lazy" if the speed to the next point exceeds a certain threshold, and removing it leads to speed below the threshold. These points are dropped.

2. Day segmenting. This algorithm has the following steps for each day of data (for a given participant).

1. **Location score.** For each GPS point X, this is a number between 0 and 1 that roughly captures the fraction of points that occur a short while after X and that are near to X. The score for a point Y is 1 if $\text{dist}(X, Y) \leq 100$ meters, and linearly decreasing from 1 to 0 if $\text{dist}(X, Y)$ is between 100 and 200 meters, and zero otherwise. If there exists at least one point Y between 1.5 and 5 minutes after X, then the sample is all points between 1.5 and 15 minutes after X, and each point is weighted using a triangular kernel (with points at 1.5, 5 and 15 minutes). If there are no points Y between 1.5 and 5 minutes after X, the sample is all points between 0 and 30 minutes after X, with triangular weights (with points at 0, 15, and 30 minutes). If there are no points Y in the 30 minutes after X, the default location score is 0.5. The location score is also calculated looking *backward* in time, with the same parameters.

[30] The accuracy radius distribution is highly bimodal. Among points below 400 meters, the vast majority are below 100 meters and most below 50 meters.

2. **Initial location and trip segments.** In this step, the algorithm iterates in reverse order through GPS points starting from the last point of the day, with a state initialized to "location." Moving from a point N to point $N-1$, the state evolves as follows. If the state of N is "location," the state of $N-1$ changes to "trip" if the (backward-looking) location score of point $N-1$ is below 0.3. If the state of N is "trip," the state of $N-1$ changes to "location" if the (backward-looking) location score of point $N-1$ is above 0.7. Otherwise, the state of $N-1$ is the same as that of N. This algorithm is relatively conservative and only switches the state if we have information consistent with the other state. A trip (location) *segment* is a sequence of points all coded "trip" ("location").
3. **Define missing data segments.** First, at this point, low-accuracy points are added back to location segments as long as the location centroid is within the accuracy radius of the low-accuracy point. (The reason is that they offer additional confirmation that the smartphone was at that location.) There are three types of missing data segments:

   - a "gap" is the period between two consecutive points that are within a "location" segment and more than 60 minutes apart.
   - a "jump" is the period between two consecutive points, the first on a "location" and the second on a "trip," which are far away: more than 1,000 meters apart, or more than 500 meters apart and 10 minutes apart. (If these conditions are false but the next point is still more than 20 minutes away, the period is labeled as a "gap.")
   - a "jumptrip" is the period between two consecutive points, the first one on a "trip" segment, that are far away: more than 2,000 meters apart, or more than 500 meters apart and more than 15 minutes apart, or more than 300 meters apart and more than 20 minutes apart.

   For each missing data segment I compute the duration and (geodesic) distance between the endpoints.

3. Classify main common locations. This proceeds in two steps. First, the algorithm clusters locations using the entire data for a given person. It uses the Density-Based Spatial Clustering of Applications with Noise algorithms, using the command `DBSCAN` in the `sklearn.cluster` package. The second step is to manually identify home and work locations starting from the most commonly visited location clusters.

Note, the main location clustering step was not used during the experiment, only for final data analysis.

4. Final locations and trip segments. In this last step, segments are combined into two main types: (final) location and (final) trip. First, each spell of consecutive location and gap segments is combined into a single location segment, and each spell of consecutive trip, jump and jumptrip segments is combined in a single trip segment. Second, the algorithm iterates over trips, starting in the morning. Each trip is expanded to include later segments one by one, until one of the following conditions holds:

- the last added segment is followed by a location with duration $M = 15$ minutes or more, or
- the destination of the last added segment is the home or the work location, or
- the destination of the last added segment is the same as the (original) trip origin.

In particular, two consecutive trips separated by a stop of 15 minutes or less will be merged into a single trip, except if the location is the home or the work location of that commuter, or if the second trip is a "return" trip.

A.3 Data Quality Measures and Analysis Sample

A.3.1 Day Data Quality Measures

To define data quality for a given day, I first compute the total duration and distance corresponding to missing data. Specifically, I compute the *total gap duration* as the total duration of gap, jump and jumptrip segments in the day, between 7 am and 9 pm. In order not overly penalize missing data during periods when the smartphone was most likely stationary, for "gap" segments, I use the segment duration minus 45 minutes, or zero, whichever is larger. The *total jump distance* is the sum of distances for all jump and jumptrip segments in the day between 7 am and 9 pm.

I define three categories of day data quality. Quality is *good* if the total gap is below 3.5 hours and the total jump below 1.5 kilometers. Quality is *medium* or *inferior* otherwise. Quality is *inferior* if the total gap is over 6.5 hours.

The analysis sample is good and medium quality days. Table SM13 shows the number and fraction of days in the sample by quality level, for three samples. In the first two columns, it considers weekdays during the experiment for the experimental sample. The middle two columns it considers the same sample of users, and all weekdays in the study (from the day when a user joined the study until the end of the study on September 11, 2017). The last two columns include the full sample of users and full sample of weekdays in the study.

Table SM13: Date data quality measures

	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	Experimental Sample Experimental Period		Experimental Sample Full Period		Full Sample Full Period	
Good quality:	7,528	0.58	18,863	0.35	36,164	0.10
Medium quality:	2,251	0.17	6,578	0.12	16,152	0.05
Inferior quality:	1,455	0.11	5,462	0.10	21,743	0.06
No data:	1,745	0.13	23,478	0.43	273,815	0.79
Total days:	12,979		54,381		347,874	
Unique users:	497		497		2301	

A.3.2 Trip Analysis Sample

The analysis sample for trips is defined according to the criteria listed in Table SM14. Overall, in the experimental sample, 64% of all non-weekend, non-holiday, daytime trips are included in the sample.

The sample and quality criteria used to construct the sample of trips are the following:

- Exclude from the sample weekends, holidays and trips before 7 am and after 10 pm.
- Exclude from the sample trips outside Bangalore. A trip is defined as outside the city if $\geq 70\%$ of the trip duration is at least 18 km from Bangalore's city center.
- Drop trips with imprecise departure time, defined as at least 15 minutes between the last point in a location and the first point on the trip. Similarly, drop trips with imprecise arrival time.
- Drop unusually short or long trips, both in terms of distance and duration.
- Drop trips for which "jumps" constitute a large part of the trip (that last at least 30 minutes or are at least 30% of the trip duration).
- Drop "swiggly" trips with a diameter (largest distance between any two points on the trip) to distance (path length) ratio of less than 0.3. These trips follow a very sinuous path.
- Drop "short loop" trips, namely trips that are overall less than 2 km and have a ratio between the origin-destination distance and the distance (path length) of less than 0.3.

Table SM14: Trip data quality measures and analysis sample

	(1)	(2)	(3)	(4)
Sample:	Experimental		Full	
1. Weekend:	51,169	0.27	0	0.00
2. Outside Bangalore:	11,423	0.06	30,966	0.11
3. Nighttime:	10,014	0.05	0	0.00
4. Imprecise departure time:	12,736	0.07	34,019	0.12
5. Imprecise arrival time:	3,746	0.02	9,358	0.03
6. Long trip (> 3 hours):	360	0.00	771	0.00
7. Long trip (> 35 km):	510	0.00	1,145	0.00
8. Short trip (< 5 minutes):	12,078	0.06	26,011	0.09
9. Short trip (< 500 meters):	1,278	0.01	3,059	0.01
10. Has jumps:	5,529	0.03	13,568	0.05
11. Swiggly:	1,976	0.01	4,220	0.02
12. Short loop trips:	4,007	0.02	8,980	0.03
13. In the analysis sample:	74,762	0.39	145,325	0.52
Total trips:	189,588		277,422	
Total days:	40,178		64,832	

A.4 Survey Data Collection Details

A.4.1 Study Recruitment

Study participants were recruited in a random sample of gas stations in South Bangalore. Gas stations are ideal locations to meet commuters who regularly use their private vehicle. (During piloting our team attempted household visits, which suffered from a very low probability of finding respondents at home.) In gas stations, surveyors worked Monday–Saturday in one of two shifts, 8 am–1 pm or 3 pm–8 pm.

Surveyors approached private vehicle drivers (commuters) who were using a car, motorcycle or scooter, excluding taxis and professional drivers, and invited them to participate in a study about understanding traffic congestion in Bangalore. After an eligibility filter, the surveyor explained in broad terms the study purpose, mentioning monetary rewards for participation and the possibility to receive monetary incentives tied to changes in travel behavior. A respondent was eligible if they reported being the owner or regular user of the private vehicle used on that day, traveling at least 20 Km in total per day, at least three days per week, owning a smartphone and not planing to leave Bangalore for more than two weeks over the following two months. Smartphone usage is very high: 76% of participants eligible based on other conditions owned a GPS Android smartphone (an additional 12% owned an iPhone and were not included). Commuters with a personal driver were included if they were the ultimate decision-maker for commuting decisions. Professional drivers (delivery person, Uber/Ola/taxi driver, etc.) were not eligible. Respondents were invited to install the study smartphone app and answer a short survey. All respondents received a study kit including a branded study flyer and consent form. Some data was collected for everyone (including commuters who refused the survey): perceived age category, gender, and vehicle information.

Out of 16,911 persons approached, 43% refused to be interviewed. A further 28% were ineligible. 2,299 installed the app, an estimated 27% of all eligible respondents.

In the weeks after recruitment, the study collected travel data from the participant smartphone app. The study team monitored quality and contacted respondents in case data quality problems arose. Participants were offered an incentive worth 300 INR in phone recharge for providing one week of quality data.

A.4.2 Hypothetical Choice Questions

The "stated preferences" phone survey collected data on typical departure times and travel times, beliefs about travel times at earlier and later times, as well as hypothetical choice questions for route choice and departure time in the presence of congestion charges. These two types of questions were designed to be similar to the two experiments:

> ***Value of Time Questions.*** *Imagine there were two different routes to go from home-to-work. The routes are identical: same distance, same road quality, etc. The only difference is that one route is faster, but it has a charge (toll) that you must pay. The other route is slower but it's free.*
>
> *One route takes T_0 minutes and has a charge. The other route takes $T_1 = T_0 + \Delta T$ minutes and no charge. This route takes ΔT minutes more.*
>
> *[Surveyor asks for each of $p^R \in \{\text{INR}100, 90, \ldots, 30, 25, 20, 15, 10, \}$]*
>
> *Please tell me, what do you prefer: T_0 minutes and paying p^R or T_1 minutes for free?*
>
> ***Schedule Flexibility Questions.*** *Now please imagine that there is a toll on your usual route, and the toll is different at different times. Imagine that everything else on the route is the same as your usual route. We would like to know if you would change your departure time to avail of a lower toll.*
>
> *The toll is p^D Rs for leaving at your usual departure time, h. If you leave [**direction**] it is less expensive. For example:*
>
> - *If you leave 5 minutes [**direction**], you save $\Delta p^D \cdot 5$ Rs (toll is $p^D + \Delta p^D \cdot 5$ Rs).*
> - *If you leave 10 minutes [**direction**], you save $\Delta p^D \cdot 10$ Rs (toll is $p^D + \Delta p^D \cdot 10$ Rs).*
> - *If you leave 20 minutes [**direction**], you save $\Delta p^D \cdot 20$ Rs (toll is $p^D + \Delta p^D \cdot 20$ Rs), and so on.*
>
> *Leaving [**other-direction**] is more expensive, with the same amounts. For every minute that you leave [**direction**], you pay less.*
>
> *Q1. Based on this information, would you change your departure time?*
>
> - *Yes: I would leave earlier*
> - *No: I would leave at the same time*
> - *Yes: I would leave later*
>
> *Q2. How much earlier/later would you leave, on average? (in minutes) [integer]*

All questions had specific numbers, partly based on previous responses (e.g. T_0, h). [**direction**] was randomly chosen to be either "earlier" or "later."

A.5 Experimental Congestion Charge Platform

The experimental sample was selected based on app data quality and a second eligibility check. Commuters with less than 5km of travel per day, and those who actually lived or spent considerable amount of time outside Bangalore, were dropped. All participants (including the control group) met in person with a surveyor at a location convenient for the respondent. After the meeting was scheduled and before it took place, participants were randomized into treatments. During the meeting, surveyors explained the treatment and (if applicable) how congestion charges function.

Participants also received support materials such as a laminated rate card with information about congestion charges (see Figure A2). Overall, 497 (22% of all app participants) were enrolled in the experiment on a rolling basis.

During the experiment, congestion charges were deducted from a pre-paid virtual account. The outstanding balance at the end of each week during the experiment was transferred to the participant's bank account. Participants were also charged a fee for severely incomplete GPS data, and if they did not make any trips on a given weekday. The "no trip" fee was designed to dissuade incentive gaming by leaving the smartphone at home for the entire day. A maximum daily total charge and minimum account balance of 250 INR also applied. Account opening balances were chosen separately for each participant, based on a model that predicted expected charges given baseline travel behavior and a hypothesized responsiveness to treatment. The target final account balance was randomized to either 500 INR or 1,000 INR per week. To establish trust, participants received a welcome bank transfer soon after the first meeting, and/or an external smartphone battery (power bank) as a gift during the meeting. A study call center was available if study participants had questions or complaints.

During the initial meeting, surveyors framed the account balance as the "respondent's money," and congestion charge as losses. During the experiment, charges were computed automatically and participants received daily account balance updates through SMS and app notifications. In addition, weekly phone calls reminded participants about their treatment group details. These features were designed to ensure salience of the congestion charges, which affects demand elasticities (Finkelstein, 2009).

Experimenter demand effects are an important concern in this setting. Commuters in Bangalore generally care deeply about traffic congestion, and study participants may be motivated to avoid congested times or areas by a sense of civic duty. While these responses may in principle be real, it is also possible that they are specific to this (short-term) experiment, where their participation was voluntary and compensated. To guard against experimenter demand effects, during the meeting, surveyors presented options in a neutral light, and emphasized at least twice that the study does not have a preference over whether participants change or do not change their behavior.

Before the start of the congestion charge phase, participants underwent a three-day *trial phase* where they received congestion charge messages to understand how charging works.

Route Congestion Charge Experiment. After the experiment, eleven route treatment participants were dropped because the chosen area overlapped with one of their baseline stable destinations.

To create random variation in the induced detour, for each participant I selected multiple candidate congestion areas and computed the detour for each. Long (short) detour areas induced a predicted detour between 7 and 14 minutes (between 3 and 7 minutes) longer than the usual route. Participants were randomized into short/long detour groups, and the area to be implemented was randomly chosen from that group, if possible. If a participant assigned to the long detour group only had a viable area with a short detour, that area was implemented.

The experiment was generally successful in terms of *retaining* study participants: approximately 5% of participants dropped out right after the meeting, and this figure rose to 10% on the last day of the study. Drop outs are 2 percentage points more frequent in the treatment group, but this difference is not statistically significant (p-value 0.20).

A.6 Randomization Details

The randomization strata were all eight combinations of area eligible/ineligible, car/motorcycle or scooter, high/low kilometer travel at baseline. Participants were assigned to treatment on a rolling basis, and the treatment allocation was pre-randomized within each stratum. This was done differently for strata that were area eligible than those that were area ineligible.

In each of the four strata for area ineligible participants, blocks of 24 consecutive positions were perfectly balanced for all (8) combinations of 4 departure time sub-treatments and early/late timing. The departure time sub-treatment probabilities are shown in panel A in Appendix Table SM2. The early/late groups were equal probability. Randomization was implemented by choosing a random permutation of $\{1, 2, \ldots, 24\}$ for each block of 24 positions.

In each of the four strata for route eligible participants, blocks of 64 consecutive positions were perfectly balanced for all (32) combinations of 4 departure time sub-treatments and 8 route sub-treatments (all combinations of early/late, high/low rate, long/short detour). The departure time sub-treatment probabilities are shown in panel A in Appendix Table SM2. The route sub-treatments were equal probability. In addition, within the 64 positions, blocks of 8 consecutive positions were balanced on the "marginals" for the (8) route sub-treatments, and for the (4) departure time sub-treatments. This restriction generates approximate stratification by enrollment time. Randomization was implemented for each block of 64 positions by randomly choosing a permutation of $\{1, 2, \ldots, 64\}$ that satisfies the "marginal" balance condition.

The restriction to stratify "marginals" by time is equivalent to covering the complete 8×8 bipartite graph with 8 disjoint perfect matchings. I implemented an algorithm to generate a random covering based on the proof of König's 1931 theorem.[31] The intuition is the result that in a general bipartite graph, a maximal matching can be achieved with a modified greedy algorithm. Imagine that the greedy algorithm is stuck, yet there exist two vertices in the two sides of the bipartite graph that are "exposed," namely each is connected to an edge whose other node is not covered by the current matching. Then it is possible to prove that the matching can be modified and grown by one edge via an "alternating path." This constructive proof can be used to sequentially add matchings until a full covering is found. I modified this algorithm to ensure random sampling from the set of all possible coverings.

Participants were added to the experiment on a rolling basis, and the allocation to treatments was pre-randomized for each stratum.

A.7 Additional Empirical Analysis

Some of the respondents in the route treatment in fact receive a departure time treatment in weeks when they do not get route charges. In Table A8 I restrict the entire analysis to 114 respondents in the control or information departure time sub-treatments. Results are similar and the impact is somewhat larger. The control mean is nearly identical to that Table SM7, which supports simulation results showing that departure time charges have a negligible impact on route choice. These results are consistent with mental load: participants randomly selected to receive both the route and departure time treatments (at different times) responded less to the route treatment, compared to those who only received the route treatment. For consistency with the initial experimental design, I conduct the rest of the analysis on the pooled sample. Table A5 runs equation (10) at the trip level and shows similar results. The experimental impact on trip duration is imprecise. In most specifications it is not possible to reject 6.4 minutes, the average additional duration for trips that avoid the congestion area, as predicted from Google Maps data.

A.8 Road Technology: Evidence on Bus and Truck Traffic

In 2014, the city of Bangalore banned heavy trucks from entering the city during daytime hours, from 6am to 10pm.[32] However, the level of enforcement is unclear, and official traffic police data shows that violations for "prohibition of heavy goods vehicles" account for only only 0.12% (7617 out of 6,241,923) of all violations.

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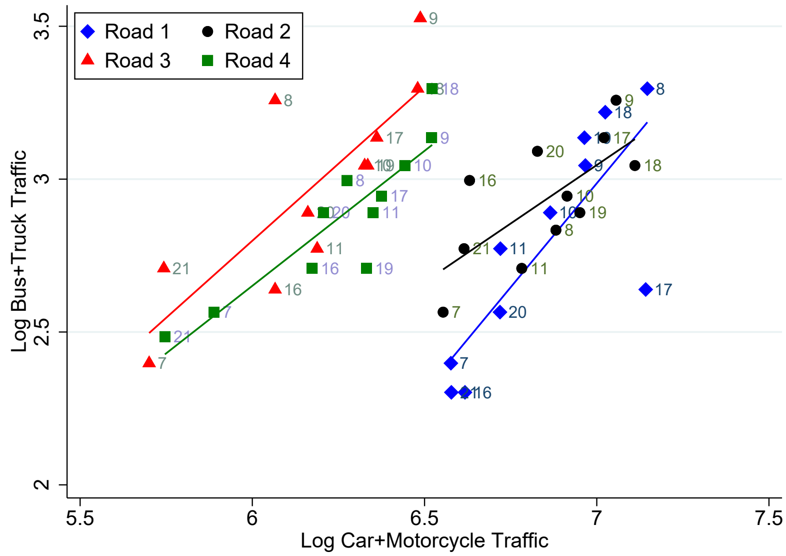
[31] I acknowledge Michel X. Goemans' lecture notes on combinatorial optimization (MIT course 18.433, 2009).

[32] see The Hindu, Heavy goods vehicles banned during the day, December 23, 2014.

To understand how truck traffic varies within day, I use data collected by a private company for a traffic impact assessment for a construction project in north Bangalore.[33] This data covers traffic flows on four roads, separately by hour of the day, and by type of vehicle (two-, three-, four-wheeler, and a category for busses and lorries). Figure SM11 shows that on each road, the two types of traffic track each other very well. A regression of log truck and bus traffic on log car and motorcycle traffic, with road fixed effects, yields a coefficient of 1.009 and within-R^2 of 0.63.

Figure SM11: Within-Day Variation: Bus and Truck Traffic Compared to Car and Motorcycle Traffic

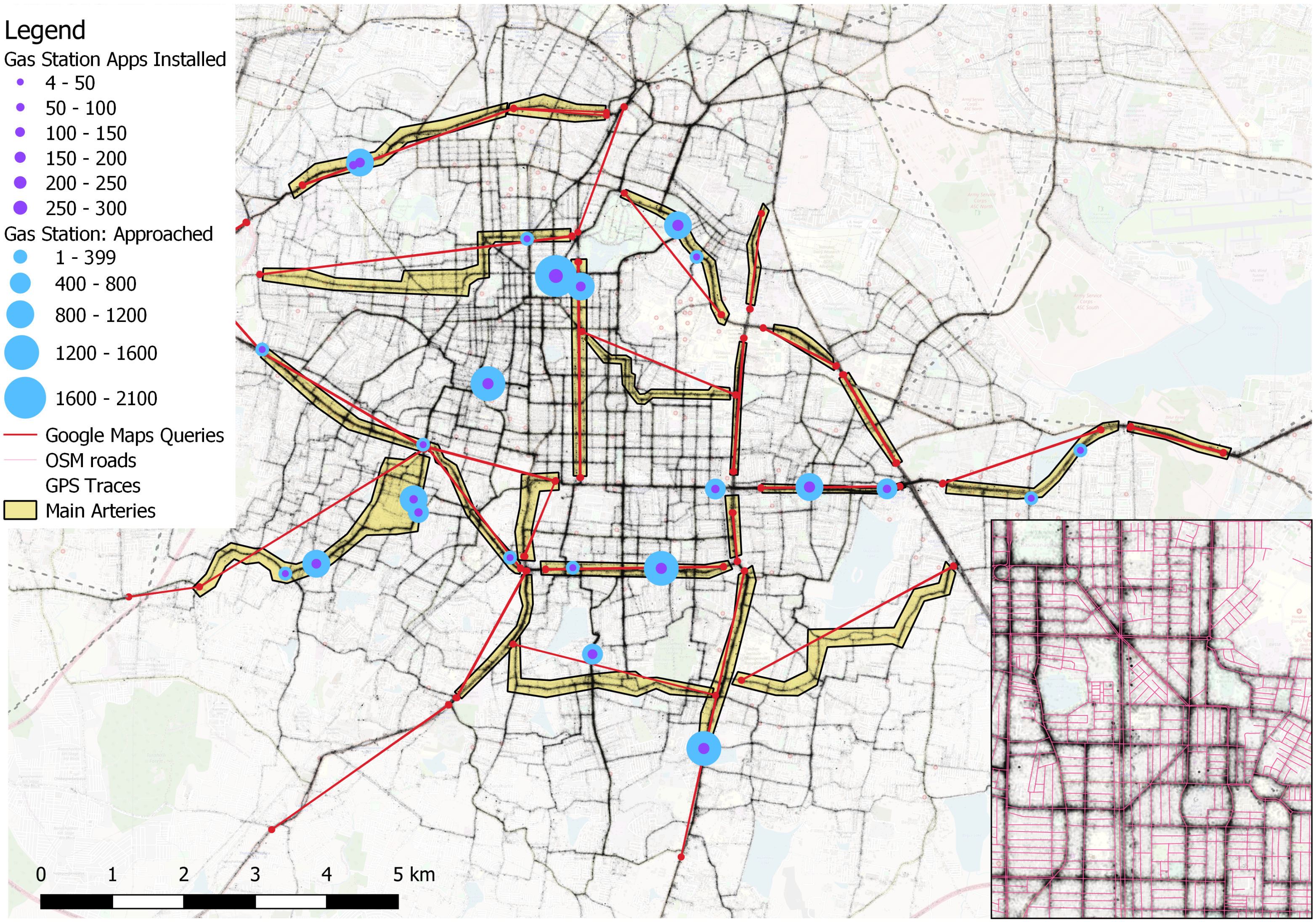


Notes. This figure compares within-day variation in traffic volumes for bus and trucks (not included in study sample) to traffic volumes for car and motorcycles (included in the study sample). Each point represents an hour of the day. The sample only includes hours 7am-12pm and 4pm-9pm.

A.9 Online Appendix: Figures

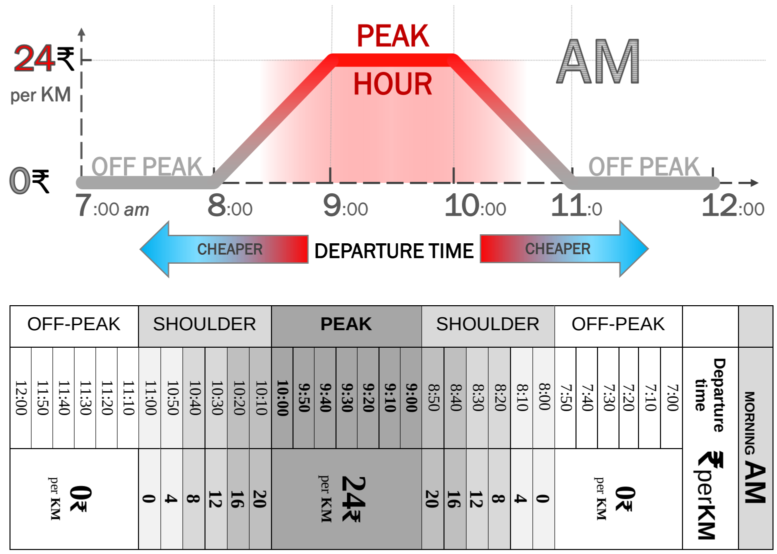
[33] Traffic Density Assessment Report (2017), Consortia of Infrastructure Engineers, available at `http://environmentclearance.nic.in/writereaddata/Form-2FB/Infra/07032019K01VPRJ5TrafficStudy.pdf`

Figure A1: Study Area and Recruitment Locations



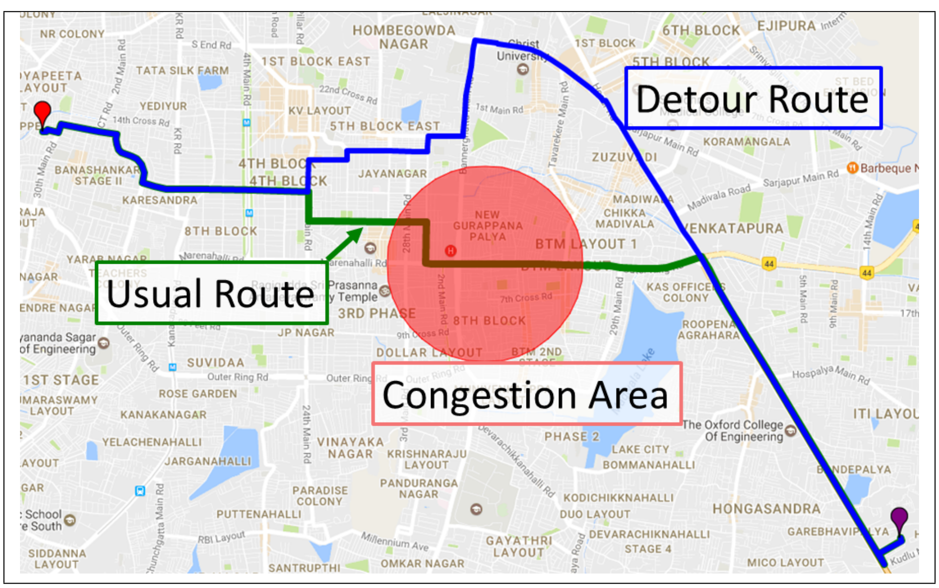
Notes. This figure shows the study area in South Bangalore. Blue and purple discs represent the randomly chosen gas stations where study participants were recruited (the blue diameter indicates the number of commuters approached, and the purple diameter the number of apps successfully installed). The black points in the background represent all the GPS data collected during the study. The red straight lines connect origin and destination pairs corresponding to the Google Maps queries used in Figure 1 (queries are done in both directions). (The dashed gray lines correspond to queries in other parts of the city, which are not used here.) The light yellow areas correspond to major arteries used in the road technology analysis in Appendix Figure SM7.

Figure A2: Departure Time Congestion Charge (AM) Rate Profile Card Example



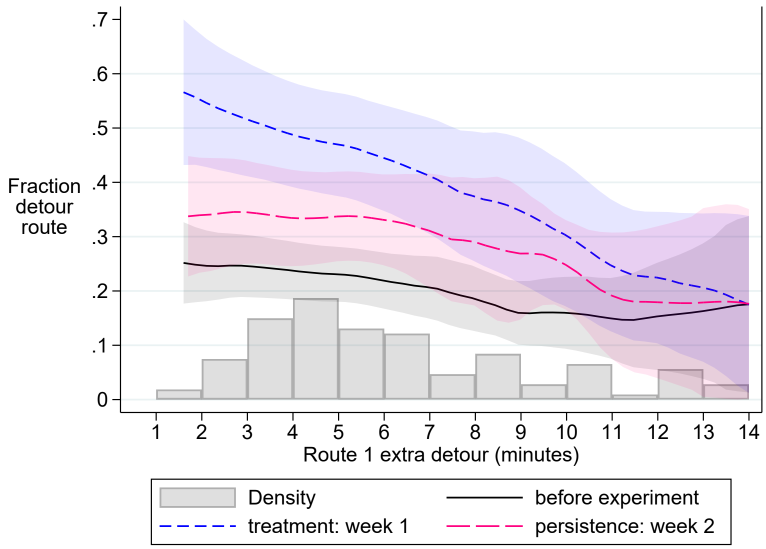
Notes: This figure shows an example of Rate Profile card that study participants in the departure time charge sub-treatments received. The cards for different participants differed in the value of the *peak rate* (12 INR/Km and 24 INR/Km in the Low Rate and High Rate sub-treatments, respectively), and in the starting time of the profile (between 8 am and 9 am for AM, and between 5 pm and 6 pm for PM).

Figure A3: Route Congestion Charge Map Example



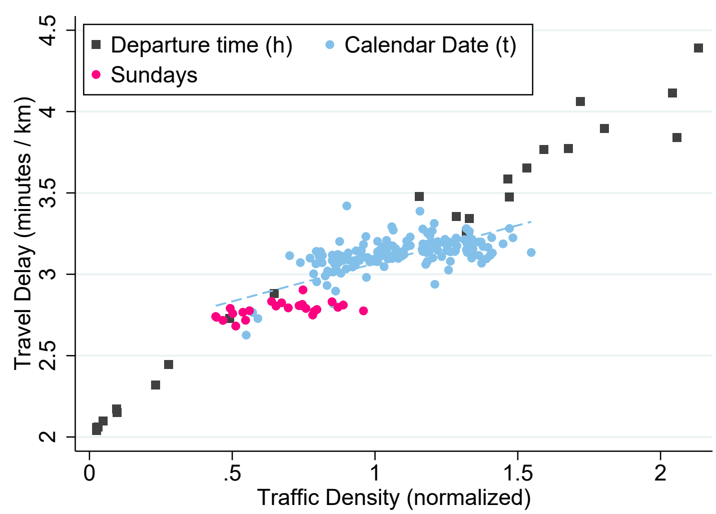
Notes: This figure shows an example of congestion area map that participants received. Congestion areas were selected as follows. Given a regular route between home and work (in green), several "candidate" areas were selected along the route, with a radius of 250m, 500m or 1000m. For each candidate area, the quickest detour route that avoids the congestion area was found using a custom algorithm using multiple Google Maps API queries. Candidate areas with detours between 3 and 14 minutes longer were manually reviewed, and the final area was randomly selected from within this group.

Figure A4: Impact of Route Charges on Detour Route Usage: Heterogeneity by Detour Duration



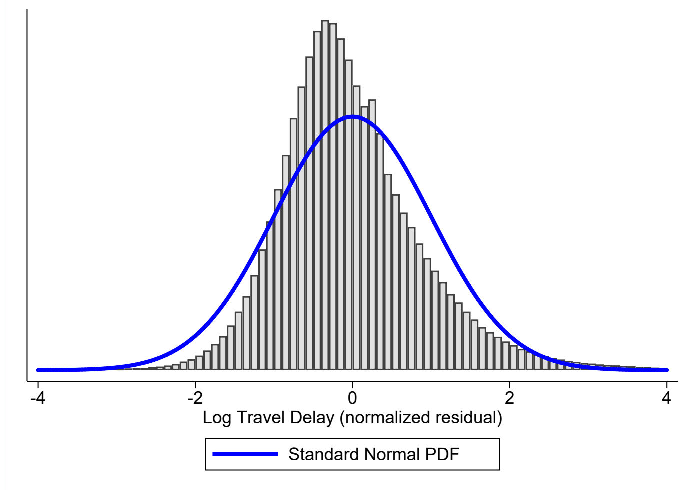
Notes. This figure plots detour route usage as a function of detour duration (the travel time difference between $r = 1$ and $r = 0$ at 9 am), for the early route treatment group, before the experiment (black, solid line), in week 1 when charges are in effect (blue, dashed line) and in week 2 after charges end (red, long dash line). The sample is frequent commuters in the "early" route treatment with detours less than 15 minutes (107 commuters). The sample consists of all home-to-work trips and the outcome is whether the trip used a detour route (defined as any route that avoids the congestion area). The sample covers all non-holiday weekdays with good quality GPS data, excluding days outside Bangalore. In the post period, all days except trial days are included. I average the outcome within for each commuter and time period, and then for each series I plot a local linear regression of detour usage on route 1 detour.

Figure A5: Road Technology: Travel Delay and Traffic Density over Dates



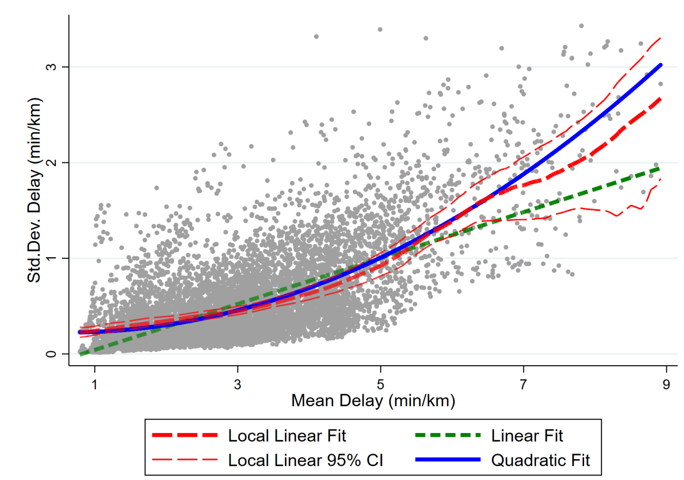
Notes: This graph shows how calendar date-level travel delay and density of traffic are related. Data is as in Figure 4, and includes weekends. For each date I compute average density per capita (using the number of app users that week). I compute the average delay over all routes and departure times, for each day in the data. Table 3 column 4 reports the regression version of this relationship.

Figure A6: Google Maps Travel Time is Approximately Log-Linear Distributed



Notes: This figure shows the shape of the day-to-day variation of log normalized travel time. For each route and departure time cell, I consider the distribution of travel times over 145 weekdays. Within each cell, I compute the normalized residual by subtracting the mean and dividing by the standard deviation for that cell. The graph shows the distribution of the log residuals for all cells, and a standard normal (solid blue line).

Figure A7: Travel Time Standard Deviation is Approximately Quadratic in Travel Time Mean



Notes: This figure shows the relationship between the mean and standard deviation of travel time. Each dot represents a route and departure time cell, and the two axes measure the mean and standard deviation in that cell over over weekdays. The local linear, linear and quadratic fits are respectively shown in red (long dash), green (dash) and blue (solid). The local linear fit uses an Epanechnikov kernel with 0.5 minute per kilometer bandwidth and 95% confidence intervals bootstrapped by route, are also shown (thin red dashed line). The estimated quadratic equation is:

$$\text{StdDevDelay} = \underset{(0.02)}{0.24} - \underset{(0.01)}{0.05} \cdot \text{MeanDelay} + \underset{(0.002)}{0.04} \cdot \text{MeanDelay}^2$$

A.10 Online Appendix: Tables

Table A1: Measures of attention to the experiment

	Departure Time				Route	
	(1)	(2)	(3)	(4)	(5)	(6)
Low Wage	-0.00	0.01	0.02	0.02	-0.09	-0.08
	(0.07)	(0.07)	(0.06)	(0.03)	(0.09)	(0.09)
Constant	0.59***	0.57***	0.55***	0.05**	0.59***	0.52***
	(0.06)	(0.05)	(0.04)	(0.02)	(0.06)	(0.06)
Outcome Measure	Charges are per-KM	Rate is fun of dep time	Peak rate correct	2/3 correct	Knows area location	Daily charges correct ($\geq$ 4/5 days)
Observations	272	272	272	272	114	114
Participants	110	110	110	110	114	114

Notes: This table report results from a phone survey with treatment group study participants. It took place after the initial in-person meeting (when a surveyor explained the treatments), either during or up to a week before the respective treatment started. The dependent variable in each regression is a dummy for below-median self-reported monthly income. The main outcome measure in each column is a dummy for whether the respondent correctly identified a certain aspects of their treatment. Columns 1-4 report the fraction of respondents who correctly and unprompted identified that congestion charges are proportional to trip length, that they depend on when the trip starts, and the maximum rate (12 INR or 24 INR). Columns 5 and 6 report the fraction of respondents who correctly described the congestion area location, and correctly identified the route charges for at least four out of five days.

Table A2: Impact Over Time of Charges on Daily Total Hypothetical Rate

	(1)	(2)
	DT Charges Hypothetical	Route Charges Hypothetical
DT Charges	-10.58**	
	(4.18)	
DT Charges × Trend	-2.29	
	(2.90)	
Route Charges		-30.35***
		(9.13)
Route Charges × Trend		1.40
		(3.47)
Observations	15,585	9,809
Control Mean	95.74	74.68

Notes: This table reports the impact of departure time chargs (column 1) and route charges (column 2) on daily total hypothetical charges, by time in the experiment. "Trend" captures centered time in the experiment, week= $-1, 0, 1$ in column 1, and day=$-2, -1, 0, 1, 2$ in column 2. In column 2, the sample is restricted to the first week in the experiment and the specification includes day in the experiment FE. $^{*}p \leq 0.10$, $^{**}p \leq 0.05$, $^{***}p \leq 0.01$

Table A3: Impact of Departure Time Charges on Daily Total Hypothetical Rate

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Time of Day	AM & PM		AM			PM	
		all	pre peak	post peak	all	pre peak	post peak
Commuter FE	X	X	X	X	X	X	X
Panel A. Full Sample							
Charges × Post	-10.55**	-5.28**	-3.12*	-2.17	-5.27**	-2.42	-2.84*
	(4.18)	(2.51)	(1.73)	(1.49)	(2.57)	(1.78)	(1.57)
Post	0.65	-1.19	0.29	-1.48	1.84	1.61	0.23
	(3.94)	(2.38)	(1.65)	(1.50)	(2.54)	(1.79)	(1.57)
Observations	15,585	15,585	15,585	15,585	15,585	15,585	15,585
Control Mean	95.74	46.89	23.81	23.08	48.85	24.60	24.25
Panel B. Regular Commuters, Home-Work and Work-Home Trips							
Charges × Post	-7.94***	-3.76**	-3.00*	-0.76	-4.18**	-0.88	-3.30***
	(2.89)	(1.90)	(1.56)	(1.20)	(1.67)	(1.23)	(1.08)
Post	-1.74	-0.74	-1.29	0.55	-1.00	-0.69	-0.31
	(2.65)	(1.74)	(1.30)	(1.36)	(1.61)	(1.18)	(1.06)
Observations	12,115	12,115	12,115	12,115	12,115	12,115	12,115
Control Mean	40.80	23.37	14.27	9.10	17.44	9.15	8.29
Panel C. Variable Commuters, All Trips							
Charges × Post	-5.17	-2.18	1.63	-3.81	-2.98	-5.36	2.37
	(8.50)	(5.18)	(3.10)	(3.36)	(5.78)	(3.83)	(3.78)
Post	1.67	1.10	1.52	-0.41	0.57	2.62	-2.04
	(7.67)	(4.67)	(3.00)	(3.75)	(5.13)	(3.91)	(3.23)
Observations	2,917	2,917	2,917	2,917	2,917	2,917	2,917
Control Mean	87.17	38.21	16.87	21.35	48.95	25.99	22.96

Notes: This table reports difference-in-differences impacts of the departure time congestion charges on daily total hypothetical rates. Overall, the sample of users and days, and the specifications, are the same as in Table 1, panel B. Columns (3) and (6) restrict to trips before the peak, i.e. the mid-point of the rate profile. Columns (4) and (7) restrict to trips after the peak. Panel B restricts to regular commuters and direct trips between their home and work locations (in either direction), and panel C restricts to variable commuters. Standard errors in parentheses are clustered at the respondent level . $^{*}p \leq 0.10$, $^{**}p \leq 0.05$, $^{***}p \leq 0.01$

Table A4: Impact of Departure Time Charges on Trip Departure Times

	(1)	(2)	(3)	(4)
Time of Day	AM		PM	
	pre peak	post peak	pre peak	post peak
Commuter FE	X	X	X	X
Panel A. Departure Time (minutes) – All Trips				
Charges × Post	-3.0*	2.8*	-0.3	2.2
	(1.7)	(1.6)	(1.6)	(1.5)
Observations	5,939	5,047	5,596	5,478
Panel B. Number of Trips – All Trips				
Charges × Post	-0.01	-0.01	-0.02	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)
Observations	15,585	15,585	15,585	15,585
Control Mean	0.28	0.25	0.27	0.24
Panel C. Departure Time (minutes) – Home-Work Trips				
Charges × Post	-3.8*	5.6	4.2	7.1**
	(2.0)	(3.4)	(3.6)	(3.0)
Commuter Sample	X	X	X	X
Observations	3,003	1,328	1,613	1,423
Panel D. Number of Trips – Home-Work Trips				
Charges × Post	-0.01	-0.00	-0.01	-0.02
	(0.02)	(0.01)	(0.01)	(0.01)
Commuter Sample	X	X	X	X
Observations	12,115	12,115	12,115	12,115
Control Mean	0.21	0.10	0.11	0.09

Notes: This table reports the impact of the departure time congestion charges treatment on departure times (panels A and C) and the number of trips, for trips taking place during the pre- and post-peak “ramps” in the morning and evening. Panels A and B use all (good quality) trips and users, while panels C and D restrict to regular commuters and trips between home and work or vice-versa. The sample in column 1 is all trips between 1.5 and 0.5 hours before the ramp midpoint for that commuter, in the morning. This interval corresponds to the early AM “ramp” when the congestion rate is linearly increasing. The outcomes in the other columns are defined analogously.

Table A5: Impact of Route Charges on Trip Duration and Trip Hypothetical Charge

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Outcome	*Trip Hypothetical Charge*		*Trip Duration (minutes)*			*Trip Duration truncated at 99% (minutes)*	
Route FE	X	X	X	X	X	X	X
Specification			IV	IV		IV	IV
Panel A. Pooled Treatment							
Treated	-22.46***	0.43			1.13*		
	(3.43)	(0.74)			(0.66)		
Avoids Area			1.90			5.03*	
			(3.10)			(2.66)	
Observations	7,489	7,489	7,483	.	7,415	7,409	
Control Mean	83.38	40.93			39.58		
P-val $\neq$ avg. detour			0.15			0.60	
Panel B. Treatment by Week							
Treated in Week 1	-18.52***	-0.60			0.31		
	(5.04)	(1.27)			(1.10)		
Treated in Week 4	-27.15***	1.18			1.70		
	(6.16)	(1.14)			(1.08)		
Avoids Area			-3.20	4.68		1.37	6.23*
			(6.70)	(3.68)		(5.55)	(3.44)
Observations	3,104	3,104	2,375	2,205	3,074	2,351	2,186
Control Mean	83.38	40.93			39.58		
P-val $\neq$ avg. detour			0.15	0.63		0.36	0.95

Notes: This table reports difference-in-differences impacts of the route treatment on trip hypothetical charge (column 1) and on trip duration (columns 2-7). The hypothetical charge of a trip is equal to 100 if the trip intersects the respondent's congestion area, and 0 otherwise. "Avoids Area" is a dummy for trips that do not intersect the area (hypothetical charge of zero). In columns 5-7 trips with duration above the 99th percentile (112 minutes) are dropped. The sample of users and days are the same as in Table SM7, except that we restrict to regular commuters and good quality, home-to-work or work to home trips. All specifications include route fixed effects. Columns 3,4,6, and 7 are 2SLS where "Avoid Area" is instrumented by the route treatment. In panel B, columns 3 and 6, week 4 is dropped from the sample, so the comparison is entirely across commuters. In panel B, columns 4 and 7, week 1 is dropped from the sample. The table also reports the p-value of equality between the coefficient on "Avoids Area" and the average extra travel time on the quickest detour route (6.4 minutes according to Google Maps). Standard errors in parentheses are clustered at the respondent level . $^{*}p \leq 0.10$, $^{**}p \leq 0.05$, $^{***}p \leq 0.01$

Table A6: Departure Time Charges Treatment Heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Heterogeneity Dummy Variable K	Regular Destination	Self Employed	Low Wage	Car Driver	Low Vehicle Value	Older	Small Stated α	Small Stated β	Short Route
Panel A. *Departure Time Treatment: Total Hypothetical Rates Today*									
Charges×Post×($K = 0$)	-11.2	-8.9	-8.9	-11.7*	-25.9***	-3.9	-10.5	-17.7**	-15.0**
	(9.2)	(5.5)	(7.4)	(6.3)	(7.4)	(7.4)	(7.8)	(7.0)	(7.2)
Charges×Post×($K = 1$)	-13.8**	-33.0**	-13.3	-16.5*	0.7	-18.4***	-15.0*	-11.2	-13.0*
	(6.0)	(12.9)	(9.1)	(8.5)	(7.4)	(6.7)	(7.7)	(8.7)	(7.0)
Observations	15,585	15,341	12,944	15,585	14,321	15,585	13,422	13,019	15,585
Participants $K = 0$	119	407	228	350	236	174	221	211	249
Participants $K = 1$	378	82	183	147	217	323	204	201	248
Control Mean $K = 0$	87.56	90.09	90.94	96.77	93.07	88.86	91.47	89.47	93.82
Control Mean $K = 1$	98.48	121.08	104.25	93.50	99.59	99.90	102.15	101.88	97.69
P-value interaction	0.81	0.09	0.71	0.65	0.01	0.15	0.68	0.56	0.85
Panel B. *Departure Time Treatment: Number of Trips Today*									
Charges×Post×($K = 0$)	-0.35	-0.06	0.01	-0.12	-0.29*	-0.08	-0.06	-0.16	-0.11
	(0.25)	(0.12)	(0.15)	(0.15)	(0.16)	(0.19)	(0.19)	(0.15)	(0.16)
Charges×Post×($K = 1$)	-0.07	-0.37	-0.27	-0.17	0.12	-0.16	-0.04	-0.09	-0.19
	(0.14)	(0.35)	(0.24)	(0.18)	(0.19)	(0.15)	(0.17)	(0.20)	(0.17)
Observations	15,585	15,341	12,944	15,585	14,321	15,585	13,422	13,019	15,585
Participants $K = 0$	119	407	228	350	236	174	221	211	249
Participants $K = 1$	378	82	183	147	217	323	204	201	248
Control Mean $K = 0$	2.95	2.78	2.83	3.01	2.78	2.88	2.89	2.81	2.76
Control Mean $K = 1$	2.95	3.70	3.23	2.82	3.09	2.99	3.08	3.11	3.14
P-value interaction	0.32	0.40	0.32	0.86	0.09	0.72	0.96	0.79	0.74

Notes: This table reports heterogeneous experimental response by observable characteristics. All heterogeneity variables K are dummy variables. They are whether the commuter:

1. has a stable destination (is a regular commuter as defined in section 5)
2. is self-employed
3. has below-median hourly wage (constructed based on self-reported monthly income)
4. is a car driver at time of recruitment
5. has a vehicle value below median (vehicle value above median includes all cars and some motorcycles)
6. is at least 35 years old
7. has stated preference value of time (α) below median
8. has stated preference schedule cost (β) below median
9. has pre-experiment home-to-work route length below median

Data. Average vehicle values are scrapped from an online marketplace in Bangalore and matched by vehicle type, brand and model. Stated preferences are from a phone survey, see section A.4.2. *Specification.* Each regression includes commuter fixed effects, study period fixed effects interacted with each group. The last line in each panel reports the p-value from the test of whether the two groups ($K = 0$ and $K = 1$) responded identically to the experiment. Inference is not adjusted for multiple hypothesis testing.

Table A7: Route Congestion Charge Treatment Heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Heterogeneity Dummy Variable K	Self Employed	Low Wage	Car Driver	Low Vehicle Value	Older	Small Stated α	Small Stated β	Short Route	Seldom Avoid Area
Panel C. *Route Treatment: Total Hypothetical Rates Today*									
Treated$\times(K=0)$	-31.7***	-45.5***	-32.5***	-21.6	-35.8**	-34.7**	-21.9	-34.1***	-22.7*
	(9.8)	(14.2)	(10.7)	(13.7)	(16.4)	(14.0)	(14.4)	(10.5)	(12.6)
Treated$\times(K=1)$	-9.6	-26.8*	-26.5	-37.1***	-27.9**	-29.3**	-35.9***	-22.6	-36.0***
	(25.9)	(14.9)	(18.6)	(13.8)	(11.4)	(13.6)	(13.3)	(18.2)	(13.1)
Observations	6,030	5,075	6,129	5,573	6,129	5,014	4,844	6,129	6,129
Participants $K=0$	204	114	174	118	79	94	92	160	117
Participants $K=1$	35	87	69	102	164	106	101	83	126
Control Mean $K=0$	110.81	130.17	113.00	115.93	116.78	107.18	86.31	128.17	84.91
Control Mean $K=1$	148.78	110.00	126.62	114.77	117.24	118.04	130.14	99.44	149.57
P-value interaction	0.42	0.37	0.78	0.43	0.69	0.78	0.48	0.59	0.46
Panel D. *Route Treatment: Number of Trips Today*									
Treated$\times(K=0)$	0.14	0.01	0.03	0.07	0.17	0.13	-0.05	0.01	0.15
	(0.15)	(0.20)	(0.18)	(0.18)	(0.29)	(0.20)	(0.18)	(0.13)	(0.23)
Treated$\times(K=1)$	-0.20	0.04	0.10	0.10	-0.00	0.16	0.35	0.17	-0.01
	(0.38)	(0.28)	(0.22)	(0.23)	(0.16)	(0.21)	(0.22)	(0.32)	(0.16)
Observations	6,030	5,075	6,129	5,573	6,129	5,014	4,844	6,129	6,129
Participants $K=0$	204	114	174	118	79	94	92	160	117
Participants $K=1$	35	87	69	102	164	106	101	83	126
Control Mean $K=0$	2.35	2.77	2.49	2.50	2.55	2.42	2.21	2.50	2.39
Control Mean $K=1$	3.71	2.44	2.76	2.61	2.59	2.51	2.60	2.70	2.76
P-value interaction	0.41	0.92	0.80	0.92	0.60	0.91	0.16	0.64	0.56

Notes: This table reports heterogeneous experimental response by observable characteristics. The sample includes the period before the experiment and week 1 during the experiment. All heterogeneity variables K are dummy variables. See table notes for A6. The dummy variable in the last column is whether the frequency of intersecting the congestion area pre-experiment is below median. Inference is not adjusted for multiple hypothesis testing.

Table A8: Impact of Route Charges on Daily Outcomes (D.T. Control and Info Sample)

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome	*Total Hypothetical Charges Today*			*Number of Trips Today*		
Time of Day	AM & PM	AM	PM	AM & PM	AM	PM
Commuter FE	X	X	X	X	X	X
Panel A. Pooled Treatment						
Treated	-32.24***	-20.67***	-11.56***	0.09	0.10	-0.01
	(7.94)	(4.80)	(4.34)	(0.13)	(0.08)	(0.08)
Observations	4,390	4,390	4,390	4,390	4,390	4,390
Control Mean	107.11	54.36	52.75	2.59	1.15	1.44
Panel B. Treatment by Week						
Treated in Week 1	-28.99**	-20.36***	-8.63	-0.05	0.11	-0.16
	(12.46)	(7.53)	(7.72)	(0.21)	(0.13)	(0.13)
Treated in Week 4	-34.69**	-21.07**	-13.62	0.32	0.13	0.18
	(13.85)	(8.55)	(8.27)	(0.22)	(0.12)	(0.14)
Observations	1,772	1,772	1,772	1,772	1,772	1,772
Control Mean	107.11	54.36	52.75	2.59	1.15	1.44

Notes: This table replicates Table SM7 restricting the sample to respondents in the control or information groups in the departure time treatment. The sample includes 114 respondents.

Table A9: Road Technology Trip Level Regressions

	(1)	(2)	(3)	(4)
Dependent Variable:	Trip Delay (min/km)			
Commuter FE			X	X
Traffic Density at Trip Departure Time	0.75***	0.73***	0.62***	0.60***
	(0.03)	(0.02)	(0.02)	(0.02)
Trip Length (km)		-0.05***		-0.02***
		(0.00)		(0.00)
Constant	2.61***	3.11***	2.88***	3.09***
	(0.05)	(0.05)	(0.03)	(0.04)
Observations	81,193	81,193	81,193	81,193

Notes: This table reports trip-level quantile (median) regressions of the trip delay (trip duration divided by trip length in minutes/kilometers) on average traffic density at the trip departure time, and on trip length. The sample is all weekday trips more than 2km in length, without any stops along the way, and with a trip diameter to total length ratio above 0.6 (the 25th percentile). Columns 3 and 4 first residualize the trip delay on commuter fixed effects. Standard errors in parentheses are clustered at the commuter level. $^{*}p \leq 0.10$, $^{**}p \leq 0.05$, $^{***}p \leq 0.01$

Table A10: Road Technology: Travel Delay Linear in Traffic Density

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	Travel Delay GPS Data (min/km)				
Sample:	Date × Dep Time (th)		Dep Hour (h)		Date (t)
	6am-10pm				
Specification:	2SLS	2SLS	OLS	NLS	OLS
Traffic Density	0.79***	0.61***	0.86***	1.36***	0.35***
	(0.03)	(0.03)	(0.08)	(0.22)	(0.05)
Traffic Density Exponent ν				0.52***	
				(0.17)	
Constant	2.72***	3.07***	2.72***	2.37***	3.66***
	(0.04)	(0.04)	(0.10)	(0.19)	(0.04)
Observations	2,876	2,255	24	24	185
Effective F-Stat	522.8	338.4			
Critical value 5%	32.9	30.7			
Traffic Density Std. Dev.	0.86	0.86	0.76	0.76	0.24
$Adj.R^2$			0.92	0.95	0.32

Notes: version of Table 3 using travel delay based on GPS data rather than Google Maps. To compute travel delay from GPS trips, the sample is all weekday trips more than 2 kilometers long, without stops along the way, and with a trip diameter to total length ratio above 0.6 (the 25th percentile). For each hour-day I compute the average travel delay over trips starting in that interval.