SM Supplementary Material for "Peak-Hour Road Congestion Pricing: Experimental Evidence and Equilibrium Implications"

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SM.1 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.[75]
- *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

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

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.

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.

SM.2 Data Quality Measures and Analysis Sample

SM.2.1 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 A12 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 A12: 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	

SM.2.2 Trip Analysis Sample

The analysis sample for trips is defined according to the criteria listed in Table A13. 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 A13: 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	

SM.3 Survey Data Collection Details

SM.3.1 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* $p^R \in \{\text{Rs.}100, 90, \ldots, 30, 25, 20, 15, 10, \}$*]*
>
> *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."

SM.4 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 A2. 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.

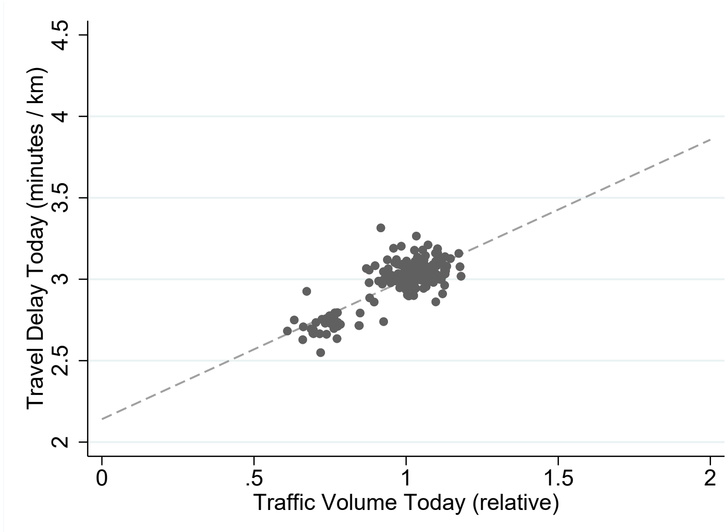
In each of the four strata for area eligible participants, blocks of 64 consecutive positions were perfectly balanced for all (32) combinations of 4 departure time sub-treatments and 8 area sub-treatments (all combinations of early/late, high/low rate, long/short detour). The departure time sub-treatment probabilities are shown in panel A in Appendix Table A2. The area sub-treatments were equal probability. In addition, within the 64 positions, blocks of 8 consecutive positions were balanced on the "marginals" for the (8) area 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.[76] 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.

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

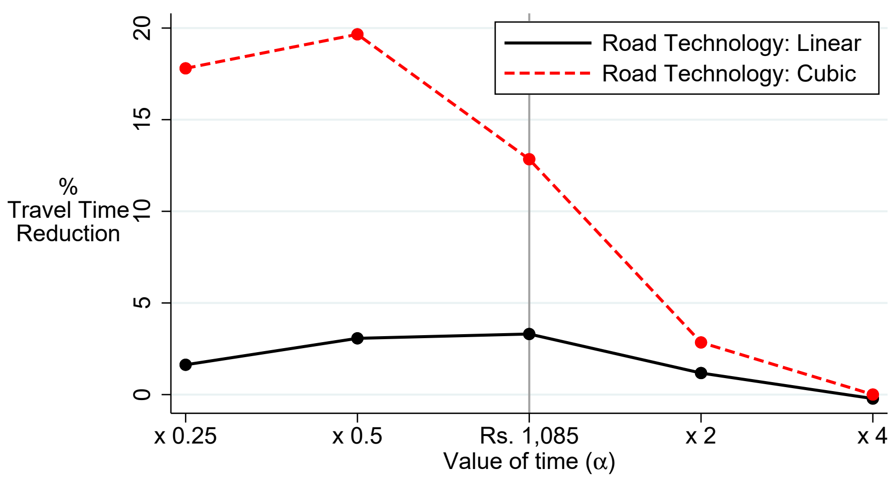
SM.5 Supplementary Material: Figures

Figure SM1: Road Technology: Travel Delay and Traffic Volume over Dates



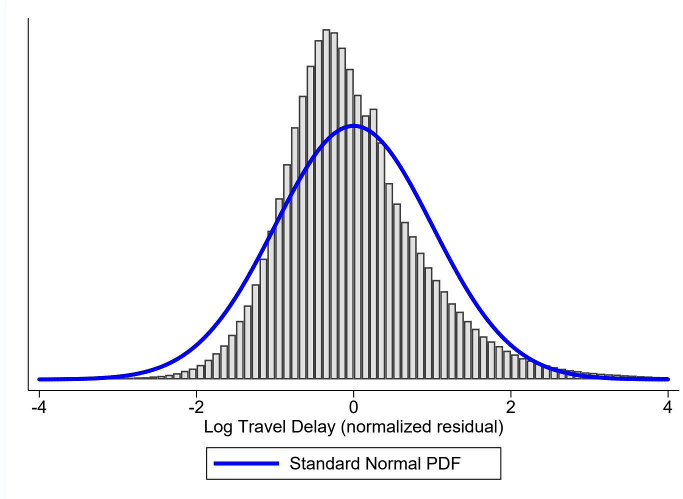
Notes: This graph shows how calendar date-level travel delay and volume of traffic are related. Data is as in Figure 3, and includes weekends. For each date I compute the number of trips per capita (using the number of app users that day), and normalize this variable to have mean 1. I compute the average delay over all routes and departure times, for each day in the data. Table 5 column 3 reports the regression version of this relationship.

Figure SM2: Policy Simulations: Varying Preference and Road Technology Parameters



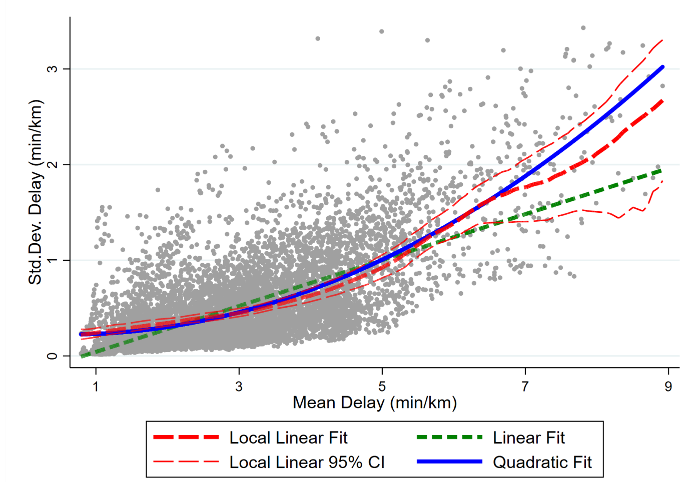
Notes: This graph replicates Figure 5 for travel time.

Figure SM3: 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 SM4: 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:

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

SM.6 Supplementary Material: Tables

Table SM1: Measures of "attention" to the experiment

	(1) Fraction Correct	(2) Observations
Panel A. Departure Time Treatment		
Charges are per-KM	61.8%	133
Rate fn of departure time	57.8%	133
Peak rate correct	55.1%	133
Two out of three correct	55.4%	133
Panel B. Area Treatment		
Knows area location	56.1%	132
Daily charges correct ($\geq 4/5$ days)	49.2%	132

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 table reports the fraction of respondents who correctly identified certain aspects of their treatment. Panel A reports 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 (Rs. 12 or Rs. 24). Panel reports the fraction of respondents who correctly described the congestion area location, and correctly identified the area charges for at least four out of five days.

Table SM2: Impact of Departure Time Charges on Daily Total Shadow 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-difference impacts of the departure time congestion charges on daily total shadow 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 SM3: 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)				
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				
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)				
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				
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 SM4: Impact of Area Charges on Trip Duration and Trip Shadow Charge

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Outcome	*Trip Shadow 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-difference impacts of the Area treatment on trip shadow charge (column 1) and on trip duration (columns 2-7). The shadow 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 (shadow 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 3, 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 area 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 SM5: Departure Time Charges Treatment Heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9))
Heterogeneity Dummy Variable K	Regular Destination	Self Employed	Low Income	Car Driver	Low Vehicle Value	Older	Small Stated α	Small Stated β	Short Route
Panel A. *Departure Time Treatment: Total Shadow 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 4)
2. is self-employed
3. has below-median self-reported 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 Supplementary Material SM.3.1. *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 SM6: Area Congestion Charge Treatment Heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Heterogeneity Dummy Variable K	Self Employed	Low Income	Car Driver	Low Vehicle Value	Older	Small Stated α	Small Stated β	Short Route	Seldom Avoid Area
Panel C. *Area Treatment: Total Shadow Rates Today*									
Treated$\times(K=0)$	-21.5***	-28.0***	-26.6***	-20.8***	-13.7	-24.0***	-13.0	-28.9***	-12.2
	(6.0)	(8.1)	(6.5)	(7.7)	(9.4)	(7.8)	(9.2)	(6.6)	(7.6)
Treated$\times(K=1)$	-24.2*	-27.9***	-15.7	-25.7***	-28.2***	-24.8***	-32.9***	-14.8	-35.2***
	(14.4)	(8.9)	(10.3)	(8.3)	(6.8)	(8.8)	(7.7)	(10.5)	(7.9)
Observations	8,693	7,289	8,827	8,043	8,827	7,362	7,133	8,827	8,827
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 $K=0$	103.56	116.36	108.48	106.65	97.93	94.68	93.37	113.69	85.64
Control Mean $K=1$	137.78	106.67	108.30	104.86	113.61	116.37	114.78	98.34	128.48
P-value interaction	0.86	0.99	0.37	0.66	0.21	0.95	0.10	0.26	0.04
Panel D. *Area Treatment: Number of Trips Today*									
Treated$\times(K=0)$	0.18**	0.15	0.06	0.17	0.15	0.17	0.18	0.10	0.21
	(0.09)	(0.12)	(0.10)	(0.11)	(0.15)	(0.12)	(0.12)	(0.09)	(0.14)
Treated$\times(K=1)$	-0.05	0.19	0.39**	0.20	0.16	0.16	0.18	0.22	0.07
	(0.23)	(0.16)	(0.16)	(0.14)	(0.10)	(0.12)	(0.13)	(0.17)	(0.10)
Observations	8,693	7,289	8,827	8,043	8,827	7,362	7,133	8,827	8,827
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 $K=0$	2.30	2.59	2.57	2.40	2.44	2.44	2.31	2.34	2.57
Control Mean $K=1$	3.81	2.60	2.40	2.60	2.56	2.50	2.57	2.86	2.48
P-value interaction	0.34	0.86	0.08	0.88	0.96	0.95	0.99	0.57	0.41

Notes: This table reports heterogeneous experimental response by observable characteristics. All heterogeneity variables K are dummy variables. See table notes for SM5. 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.