The Welfare Effect of Road Congestion Pricing: Experimental Evidence and Equilibrium Implications

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Intro

Traffic Congestion Widespread in Large Cities

- Bangalore average speed: 9-10 miles per hour.
- Demand for travel an indicator of economic growth.
- Costs: wasted time, uncertainty, pollution, diminished agglomeration benefits.
Economists’ Approach: Price the Externality

- Traffic congestion socially inefficiently high due to driving externality
  - Focus here: driving lowers road speed
  - Theory solution: price externality, restore optimum (Pigou 1920, Vickrey 1969)
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- **Goal of this paper**: how does social optimum look like in Bangalore?
  - Eliminate congestion completely?
  - Optimal to have some congestion? If so, how much?
This paper holds the extensive margin fixed (return to this issue in simulations).

Peak-hours $1.5 \times -2 \times$ slower than nighttime
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1. Peak-hours $1.5\times-2\times$ slower than nighttime
2. Intuition: should target congestion pricing precisely
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2. Intuition: should target congestion pricing precisely
3. Short-term responses relevant
This Paper: Quantify Peak-Hour Congestion Inefficiency

Research Questions:

1. Impact of peak-hour congestion pricing on commuter departure times?

2. Impact of optimal congestion pricing on peak-hour congestion shape and commuter welfare?
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(1) Model of travel demand (departure time). Key parameters:

1. Value of time spent driving
2. Schedule costs of arriving early / late (schedule flexibility)
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(4) Measure road traffic externality, and simulate the social optimum
Preview of Results

- Commuters respond to both policies:
  - Peak-hour charges: leave earlier in AM, not later (vice-versa in PM)
  - Route charges: take detour route
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- Modest welfare gains from optimal pricing:
  - Simulation model: modest travel time benefits, mostly offset by schedule costs
  - In this setting, this conclusion driven by shape of externality
Contribution: Theory-driven Experimental Evidence

- Large theory literature in transportation economics
  - First- and second-best pricing, various margins, networks, etc.
  - Vickrey ’69, Small ’82, Arnott, de Palma, and Lindsey ’93

Evidence from real congestion pricing policies

- Reduced traffic congestion and pollution: London, Milan, Stockholm (Karlström and Franklin 2009, Simeonova et al 2018)

Welfare analysis of congestion pricing


Growing revealed preference travel demand estimation literature

- Small et al ’05, Bento et al ’17, Tillema et al ’13, Martin and Thornton ’17
  - Most studies: stated preferences (Small ’82, Ben-Akiva et al ’16)

Urban congestion literature:

- Driving restrictions (Davis ’08, Kreindler ’16, Hanna, Kreindler, Olken ’17)
- Pollution (Hanna and Oliva ’14, Gendron-Carrier et al ’17)
- Land use (Field ’05, Harari ’17)
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Plan of the Talk

2 Data and Study Sample

3 Experimental Design

4 Experimental Results

5 Externality and Policy Simulations
Data and Study Sample

Experimental Design

Experimental Results

Externality and Policy Simulations
Data & Sample Experiment Reduced Form Externality and Policy Sims

Data: GPS Traces from Smartphone App
- Android app designed for this study + automatic GPS data processing
Sample: Study Area, Recruitment in Gas Stations

Legend
- Study Area
- Gas Station Recruitment
  - 1 - 399
  - 400 - 799
  - 800 - 1199
  - 1200 - 1599
  - 1600 - 2099
- GPS Traces
Sample: Recruitment and Timeline

- Approach 8,641 eligible drivers (car and motorcycle)
  - 2,300 installed app
  - 497 experiment participants

Timeline:
- Recruitment (in gas stations)
- Initial GPS data collection
- 5 weeks randomized experiment (N=497)

Experimental platform:
- Charges deducted from initial grant
- Weekly bank transfers
- Daily SMS reports

Take part in a new research study and help us propose better traffic policies! We want to collect data about how you travel to better understand and reduce traffic in Bangalore!

- Collects information on your daily trips (time, distance, traffic).
- Uses the GPS in your phone (no other data).
- First 2 weeks: data collection only.
- You are guaranteed to receive Rs. 1,000 for participating.
- Half of all participants are randomly selected for extra incentives.
- Up to Rs. 5,000 or more if you make small changes to your travel and trips, as per our personalized advice.

Duration: 4 weeks
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**Stats**

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- Up to Rs. 5,000 or more if you make small changes to your travel and trips, as per our personalized advice.

- After 2 weeks, we will give you a personalized report, plus information on how to avoid traffic congestion.
Utility over Travel Time and Scheduling Costs

\[ u(h_D, T) = -\alpha T - \beta_E |h_D + T - h^*_A|_+ - \beta_L |h_D + T - h^*_A|_- + m \]

- Components:
  - \( h_D \): departure time (decision variable)
  - \( T = T(h_D) \): random travel time, realized after departure
  - \( m \): money (e.g. congestion charges)
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- **Components:**
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- **Preferences:**
  - \( \alpha \): value of time commuting
  - Ideal arrival time \( h^*_A \) known before departure
  - \( \beta_E, \beta_L \): cost of arriving early / late
Identifying $\alpha$, $\beta_E$, $\beta_L$ with Observational Data

$$u_i(h_{Dit}, h_{Ait}^*) = -\alpha T_{it} - \beta_E h_{Dit} + T_{it} - h_{Ait}^* - \beta_L h_{Dit} + T_{it} - h_{Ait}^* + \epsilon_{it}(h_{Dit})$$

- Panel data on departure time $h_{Dit}$
- Observed “prices”: travel time profile $T_{it}(h_D) \sim T_i(h_D)$
- Unobserved “prices”: ideal arrival time distribution $h_{Ait}^* \sim \mathcal{A}_i$
Identifying $\alpha$, $\beta_E$, $\beta_L$ with Observational Data

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- Concern: commuters who face different relative prices also have different ideal arrival times
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- Concern: commuters who face different relative prices also have different ideal arrival times
- Approach here: create experimental variation in price of $h_D$ and price of $T_{it}$
Experiment: Peak-hour Departure Time Charge

- Each trip charged with per-kilometer (variable) rate
Experiment: Peak-hour Departure Time Charge

- Each trip charged with per-kilometer (variable) rate
- Sub-treatments:
  - low rate 12 Rs/Km (~ effective Uber per-km rate in Bangalore)
  - high rate 24 Rs/Km (~ 0.4$)
  - information and nudge

![Diagram showing peak and off-peak hours with various cost rates.](image-url)
Flat charge for crossing area. This induces a detour option (longer route, but free)

Route choice informative about value of travel time

Sub-treatments:
- (A) low / high charge $p_A \in \{Rs. 80, Rs. 160\}$
- (B) short / long detour $D \in [3, 14]$ minutes
In Person Meeting to Explain Treatment
Data and Study Sample

Experimental Design

Experimental Results

Externality and Policy Simulations
Departure Times Shift Earlier (AM)

- Y axis: number of trips (change)
- Sample: all trips home to work, regular commuters only
- Control density plot
- PM results
Departure Times Shift Earlier (AM)

- Sample: all morning trips, all respondents
## Area: Daily Shadow Rates Decrease

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
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<tr>
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- Slightly higher GPS data quality in treatment group
- Similar effects throughout treatment (days 1-5)

### Data Quality

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- Structurally estimate model of morning departure time decision
  - use experimental variation from the two charges
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- Results:
  - High value of time spent driving ($4 \times$ in sample hourly wage)
  - Commuters moderately schedule flexible
## Results AM: Value of Time High vs. Early Arrival Cost

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  - Also consistent with fixed cost of switching
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- **High value of time** (4x in-sample hourly wage)
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- **Early arrival cost** $\beta_E$ low relative to value of time $\alpha$
  - Commuters have a moderate ability to adjust to congestion
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Measuring the Impact of Traffic Volume on Travel Time

- The marginal social cost on travel time $T$ at traffic volume $V$ is

$$
(T(V + 1) - T(V)) \cdot V \approx \frac{\partial T}{\partial \log V}
$$

Unit: entire trips (both for volume and for travel time)

Data:
- Volume: GPS trip data (117,527 trips, 1,747 users)
- Travel time: Google Maps data (28 fixed routes, 185 days)
- Travel time: GPS trip data

Cannot distinguish externality of motorcycle vs car
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Moderate, Linear Impact of Traffic Volume on Travel Time

- Peak-hour trip (∼ 33 min) generates ∼ 15 min aggregate travel time
Moderate, Linear Impact of Traffic Volume on Travel Time

- Peak-hour trip (~33 min) generates ~15 min aggregate travel time
- Similar: within-day and across-calendar date

Other Robust Model
Moderate, Linear Impact of Traffic Volume on Travel Time

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![Graph showing the relationship between traffic volume and travel delay]
Data & Sample Experiment Reduced Form

Literature: Lower Road Traffic Externalities at Higher Levels

- Simple bottleneck model may have huge externalities:
  - 149 minutes marginal damage for \( \approx 15 \) minute private cost (Lucas and Davis 2019)
  - Intuition: delay everyone
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- Bogota, Colombia looks similar to Bangalore (Akbar and Duranton, 2018, with similar unit and variation)
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- Couture et al (2018) find \(-0.13\) elasticity of speed to total time travelled in US cities
Citywide Traffic Equilibrium

**Goal:** citywide policy impact on traffic of (optimal) congestion charge

Two steps:

1. Road technology: how traffic volume affects travel times
2. Simulate equilibrium (with/without optimal charges)

I make strong simplifying assumptions:

- Fix home and work locations, firm schedules
- Fix travel mode, carpooling, extensive margin.
- Ignore trucks and buses (<10% of registered vehicles)
- Ignore pollution and accident externalities
Social Optimum: Notable Travel Time Benefit...

- “Best-case” social optimum: no implementation costs and all revenue redistributed lump-sum
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Social Optimum: Small Gains from Optimal Pricing

- We just saw: moderate and linear traffic externality
- This implies: modest welfare gains from optimal pricing
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  - However, low marginal externality implies travel time benefits mostly offset by schedule costs
  - In this setting, the results driven by shape of externality.
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- Similar results with other preferences, moderate heterogeneity, extensive margin.
Preferences, Externality, Heterogeneity, Extensive Margin

- Changing preferences ($\beta_E/\alpha$ ratio): welfare gains still negligible ($\leq 1\%$)
- Convex road technology: higher travel time and welfare improvements
Preferences, Externality, Heterogeneity, Extensive Margin

- Changing preferences ($\beta_E/\alpha$ ratio): welfare gains still negligible ($\leq 1\%$)
- Convex road technology: higher travel time and welfare improvements

Moderate heterogeneity in ($\alpha_i, \beta_i$): welfare gains still negligible ($\leq 1\%$)
Preferences, Externality, Heterogeneity, Extensive Margin

- Changing preferences ($\beta_E/\alpha$ ratio): welfare gains still negligible ($\leq 1\%$)

- Convex road technology: higher travel time and welfare improvements

Other Preferences, Technology

- Moderate heterogeneity in $(\alpha_i, \beta_i)$: welfare gains still negligible ($\leq 1\%$)

Preference Heterogeneity

- Incorporate extensive margin:
  - Maximum welfare gains 6.2%
  - Low welfare gains when trips valuable

Extensive Margin
Conclusion: Implications for Road Traffic Congestion

- Precisely targeted road pricing technology exists. Would it improve cities?

- In Bangalore, peak-hour pricing less attractive than believed
  - Severe congestion does not automatically imply pricing is attractive

- Other important margins:
  - pollution (generation & exposure)
  - public transit
  - firm demand for travel
Thank You!
Data: GPS Traces from Smartphone App

- Android app designed for this study
  - 76% smartphone ownership among sampling frame
  - App runs in background
- Automatic GPS data processing
  - identifying outliers
  - raw GPS → trips (start, end, route)
- Data coverage: 70–80% days
## Descriptive Statistics: Travel Behavior (GPS Data)

### Panel A. Trip Characteristics

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Obs.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Number of Trips</td>
<td></td>
<td></td>
<td>51,164</td>
</tr>
<tr>
<td>Number of Trips per Day</td>
<td>3.15</td>
<td>[1.16]</td>
<td>497</td>
</tr>
<tr>
<td>Median trip duration (minutes)</td>
<td>27.38</td>
<td>[12.77]</td>
<td>497</td>
</tr>
<tr>
<td>Median trip length (Km.)</td>
<td>7.2</td>
<td>[4.7]</td>
<td>497</td>
</tr>
</tbody>
</table>

### Panel B. Commute Destination Variability

- Regular Commuter: 0.76
- Frac. of days present at Work: 0.86
- Frac. trips Home-Work or Work-Home: 0.39

### Panel C. Departure Time Variability (Std.Dev. in hours)

- First Trip (AM): 1.24 [0.50]
- First Home to Work Trip (AM): 0.62 [0.52]

- Significant route and departure time heterogeneity
## Study Eligibility

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Approached</td>
<td>10,537</td>
<td>100%</td>
</tr>
<tr>
<td>Own vehicle</td>
<td>9,893</td>
<td>94%</td>
</tr>
<tr>
<td>Drive ≥ 3 days/wk</td>
<td>9,203</td>
<td>87%</td>
</tr>
<tr>
<td>Drive ≥ 20 km/day</td>
<td>7,398</td>
<td>70%</td>
</tr>
<tr>
<td>In Bangalore</td>
<td>7,052</td>
<td>67%</td>
</tr>
<tr>
<td>Own GPS smartphone</td>
<td>5,372</td>
<td>51%</td>
</tr>
</tbody>
</table>

- Survey “Daily Km” three times higher than measured by GPS
## Selection into Experiment

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Outcome:</strong></td>
<td><strong>Respondent In Experiment</strong></td>
<td><strong>Respondent In Experiment</strong></td>
<td><strong>Respondent In Experiment</strong></td>
<td><strong>Respondent In Experiment</strong></td>
<td><strong>Respondent In Experiment</strong></td>
<td><strong>Respondent In Experiment</strong></td>
<td><strong>Respondent In Experiment</strong></td>
</tr>
<tr>
<td>Drives Car (z-score)</td>
<td>-0.014*** (0.001)</td>
<td>-0.008*** (0.002)</td>
<td>-0.021 (0.014)</td>
<td>-0.118** (0.051)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age (z-score)</td>
<td>-0.012*** (0.001)</td>
<td>-0.007*** (0.001)</td>
<td>-0.001 (0.006)</td>
<td></td>
<td>0.016 (0.020)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log Vehicle Value (z-score)</td>
<td>-0.010*** (0.001)</td>
<td>-0.000 (0.002)</td>
<td>0.006 (0.014)</td>
<td></td>
<td>0.055 (0.052)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>KM Daily (Stated, z-score)</td>
<td></td>
<td></td>
<td></td>
<td>0.004 (0.006)</td>
<td>0.018 (0.020)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Value of Time (Stated, z-score)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.033** (0.016)</td>
<td>0.022 (0.018)</td>
<td></td>
</tr>
<tr>
<td>Schedule Flex (Stated, z-score)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.028* (0.016)</td>
<td>0.022 (0.018)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>8,227</td>
<td>8,887</td>
<td>7,200</td>
<td>7,200</td>
<td>3,670</td>
<td>952</td>
<td>777</td>
</tr>
<tr>
<td>Fraction in Experiment</td>
<td>0.06</td>
<td>0.12</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
# Selection into Experiment: Occupations

<table>
<thead>
<tr>
<th>Occupation</th>
<th>(1) In the Experiment</th>
<th>(2) Not in the Experiment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Business owner or manager</td>
<td>16.7%</td>
<td>15.6%</td>
</tr>
<tr>
<td>Accountant, Teacher, Doctor</td>
<td>7.5%</td>
<td>6.3%</td>
</tr>
<tr>
<td>Software and IT</td>
<td>10.3%</td>
<td>10.1%</td>
</tr>
<tr>
<td>Engineers, Technical</td>
<td>14.3%</td>
<td>11.2%</td>
</tr>
<tr>
<td>Office staff</td>
<td>15.4%</td>
<td>18.1%</td>
</tr>
<tr>
<td>Manual jobs</td>
<td>8.4%</td>
<td>9.5%</td>
</tr>
<tr>
<td>Mobile professions</td>
<td>15.6%</td>
<td>12.0%</td>
</tr>
<tr>
<td>Student</td>
<td>9.0%</td>
<td>13.4%</td>
</tr>
<tr>
<td>Others, Retired</td>
<td>2.9%</td>
<td>3.9%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>455</strong></td>
<td><strong>2,464</strong></td>
</tr>
</tbody>
</table>
## Travel Behavior (GPS App Data)

<table>
<thead>
<tr>
<th>Panel A. Trip Characteristics</th>
<th>(1) Median</th>
<th>(2) Mean</th>
<th>(3) Std. Dev.</th>
<th>(4) 10 Perc.</th>
<th>(5) 90 Perc.</th>
<th>(6) Obs.</th>
</tr>
</thead>
<tbody>
<tr>
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<td></td>
<td></td>
<td></td>
<td>51,164</td>
</tr>
<tr>
<td>Number of Trips per Day</td>
<td>2.85</td>
<td>3.15</td>
<td>[1.16]</td>
<td>1.90</td>
<td>4.85</td>
<td>497</td>
</tr>
<tr>
<td>Median trip duration (minutes)</td>
<td>24.50</td>
<td>27.38</td>
<td>[12.77]</td>
<td>15.05</td>
<td>42.60</td>
<td>497</td>
</tr>
<tr>
<td>Median trip length (Km.)</td>
<td>5.91</td>
<td>7.17</td>
<td>[4.66]</td>
<td>2.90</td>
<td>13.36</td>
<td>497</td>
</tr>
</tbody>
</table>

### Panel B. Commute Destination Variability

<table>
<thead>
<tr>
<th></th>
<th>(1) Median</th>
<th>(2) Mean</th>
<th>(3) Std. Dev.</th>
<th>(4) 10 Perc.</th>
<th>(5) 90 Perc.</th>
<th>(6) Obs.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regular Commuter</td>
<td></td>
<td>0.76</td>
<td></td>
<td></td>
<td></td>
<td>497</td>
</tr>
<tr>
<td>Frac. trips Home-Work, Work-Home</td>
<td>0.38</td>
<td>0.39</td>
<td>[0.21]</td>
<td>0.13</td>
<td>0.67</td>
<td>378</td>
</tr>
<tr>
<td>Frac. of trips Work-Work</td>
<td>0.03</td>
<td>0.06</td>
<td>[0.08]</td>
<td>0.00</td>
<td>0.15</td>
<td>378</td>
</tr>
<tr>
<td>Frac. of days present at Work</td>
<td>0.91</td>
<td>0.86</td>
<td>[0.16]</td>
<td>0.61</td>
<td>1.00</td>
<td>378</td>
</tr>
</tbody>
</table>

### Panel C. Departure Time Variability

(Standard Deviation of the Departure Time in hours)

<table>
<thead>
<tr>
<th></th>
<th>(1) Median</th>
<th>(2) Mean</th>
<th>(3) Std. Dev.</th>
<th>(4) 10 Perc.</th>
<th>(5) 90 Perc.</th>
<th>(6) Obs.</th>
</tr>
</thead>
<tbody>
<tr>
<td>First Trip (AM)</td>
<td>1.27</td>
<td>1.24</td>
<td>[0.50]</td>
<td>0.52</td>
<td>1.85</td>
<td>496</td>
</tr>
<tr>
<td>Last Trip (PM)</td>
<td>1.72</td>
<td>1.71</td>
<td>[0.50]</td>
<td>1.06</td>
<td>2.34</td>
<td>497</td>
</tr>
<tr>
<td>First Home to Work Trip (AM)</td>
<td>0.48</td>
<td>0.62</td>
<td>[0.52]</td>
<td>0.15</td>
<td>1.28</td>
<td>332</td>
</tr>
<tr>
<td>Last Work to Home Trip (PM)</td>
<td>0.80</td>
<td>0.94</td>
<td>[0.62]</td>
<td>0.28</td>
<td>1.78</td>
<td>321</td>
</tr>
</tbody>
</table>
Departure Time and Traffic Equilibrium Model

- General framework for urban travel demand:
  - Home and work locations (Ahlfeldt et al '15, Tsivanidis '18)
  - Mode choice: bus, carpool (McFadden '74)
Departure Time and Traffic Equilibrium Model

- General framework for urban travel demand:
  - Home and work locations (Ahlfeldt et al '15, Tsivanidis '18)
  - Mode choice: bus, carpool (McFadden '74)
  - Trip timing (scheduling) decision (Arnott, de Palma, Lindsey '93)
  - Route choice
Departure Time and Traffic Equilibrium Model

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  - Home and work locations (Ahlfeldt et al '15, Tsivanidis '18)
  - Mode choice: bus, carpool (McFadden '74)
  - **Trip timing (scheduling) decision** (Arnott, de Palma, Lindsey '93)
  - Route choice

- Setting: home to work commuter

- Environment: distribution of travel time at each departure time
Utility over Travel Time and Scheduling Costs

\[ u(h_D, T) = -\alpha T - \beta_E |h_D + T - h^*_A|_\text{time early} - \beta_L |h_D + T - h^*_A|_\text{time late} + m \]

- Components:
  - \( h_D \) departure time (decision variable)
  - \( T = T(h_D) \) random travel time, realized after departure
  - \( m \) money (e.g. congestion charges)
Utility over Travel Time and Scheduling Costs

\[ u(h_D, T) = -\alpha T - \beta_E |h_D + T - h_A^*|_+ - \beta_L |h_D + T - h_A^*|_- + m \]

- **Components:**
  - \( h_D \): departure time (decision variable)
  - \( T = T(h_D) \): random travel time, realized after departure
  - \( m \): money (e.g. congestion charges)

- **Preferences:**
  - \( \alpha \): value of time commuting
  - Ideal arrival time \( h_A^* \) known before departure
  - \( \beta_E, \beta_L \): cost of arriving early / late

Graph
Nonparametric Identification
Identifying $\alpha$, $\beta_E$, $\beta_L$ with Observational Data

$$u_i(h_D, h_{Ait}^*) = -\alpha T_{it} - \beta_E | h_D + T_{it} - h_{Ait}^* | - - \beta_L | h_D + T_{it} - h_{Ait}^* | + \varepsilon_{it}(h_D)$$

- Heterogeneity:
  - In principle can accommodate $\alpha_i$, $\beta_{Ei}$, $\beta_{Li}$
  - $\varepsilon_{it}(h_D)$ extreme value distributed
Identifying $\alpha$, $\beta_E$, $\beta_L$ with Observational Data

$$u_i(h_D, h^{*}_{Ait}) = -\alpha T_{it} - \beta_E |h_D + T_{it} - h^{*}_{Ait}| - \beta_L |h_D + T_{it} - h^{*}_{Ait}| + \epsilon_{it}(h_D)$$

- **Heterogeneity:**
  - In principle can accommodate $\alpha_i$, $\beta_{Ei}$, $\beta_{Li}$
  - $\epsilon_{it}(h_D)$ extreme value distributed

- **Identification challenge with observational data:** price endogeneity
  - Observed “prices”: travel time profile $T_{it}(h_D) \sim T_i(h_D)$
  - Unobserved “prices”: ideal arrival time distribution $h^{*}_{Ait} \sim A_i$
Identifying $\alpha, \beta_E, \beta_L$ with Observational Data

\[ u_i(h_D, h^*_A it) = -\alpha T_{it} - \beta_E |h_D + T_{it} - h^*_A it| - \beta_L |h_D + T_{it} - h^*_A it| + \varepsilon_{it}(h_D) \]

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  - In principle can accommodate $\alpha_i, \beta_{Ei}, \beta_{Li}$
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- **Identification challenge with observational data: price endogeneity**
  - Observed “prices”: travel time profile $T_{it}(h_D) \overset{iid}{\sim} T_i(h_D)$
  - Unobserved “prices”: ideal arrival time distribution $h^*_A it \overset{iid}{\sim} A_i$

- Approach here: create experimental variation in price of $h_D$ and price of $T_{it}$
**Departure Time Information Sub-Treatment**

![Traffic Congestion in Bangalore by weekday and time of day](image)

- **Daily SMS reports:**
- **Lower travel time recommendations (earlier/later)**
Randomized Experiment Design

- Two main treatment arms:
  - **Departure time**: High/Low Rate, Information, Control
  - **Area**: High/Low Charge, Short/Long Detour

Approx 50-60% aware of treatment during follow-up calls

Other Design Information

Design Matrix
Randomized Experiment Design

- Two main treatment arms:
  - **Departure time**: High/Low Rate, Information, Control
  - **Area**: High/Low Charge, Short/Long Detour

- Sequential, cross-randomized, sub-treatments:
  - **Area** (1 week), then **Departure Time** (3 weeks)
    OR
  - **Departure Time** (3 weeks), then **Area** (1 week)

Approximately 50-60% aware of treatment during follow-up calls
Randomized Experiment Design

- Two main treatment arms:
  - **Departure time**: High/Low Rate, Information, Control
  - **Area**: High/Low Charge, Short/Long Detour

- Sequential, cross-randomized, sub-treatments:
  - **Area** (1 week), then **Departure Time** (3 weeks)
  - OR
  - **Departure Time** (3 weeks), then **Area** (1 week)

- Approx 50-60% aware of treatment during follow-up calls

Other Design Information
Design Matrix
Back
Additional Experimental Design Features

- Stratified by: car vs motorcycle, area eligibility, and average daily kilometers
  - "high kilometers" strata more likely to receive "Low Rate" treatment (25% – 75%) and vice versa
- Three days “trial period” before congestion charge treatments (area/departure time)
- Additional area Sub-treatment:
  - 2 randomly chosen days (out of 5) had 50% higher rate
- Cross-randomization further balanced across time:
  - Each block of 8 consecutive balanced on marginals (DT, Area)
  - Problem: cover complete $8 \times 8$ bipartite graph with 8 perfect matchings (randomly)
  - Solution: augmenting path algorithm to select matchings (König 1931)
## Experimental Design Matrix

<table>
<thead>
<tr>
<th>Week</th>
<th>Control</th>
<th>Information</th>
<th>Low Rate</th>
<th>High Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Strata 1-4</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>AREA</td>
<td>AREA</td>
<td>low rate</td>
<td>AREA</td>
</tr>
<tr>
<td>2</td>
<td>control</td>
<td>info</td>
<td>low rate</td>
<td>high rate</td>
</tr>
<tr>
<td>3</td>
<td>control</td>
<td>info</td>
<td>low rate</td>
<td>high rate</td>
</tr>
<tr>
<td>4</td>
<td>control</td>
<td>AREA</td>
<td>low rate</td>
<td>high rate</td>
</tr>
</tbody>
</table>

| Strata 5-8 |          |             |            |            |
| 1          | control  | info        | low rate   | info       |
| 2          | control  | info        | low rate   | high rate  |
| 3          | control  | info        | low rate   | high rate  |
| 4          | control  | info        | low rate   | info       |
## Selection into Experiment

<table>
<thead>
<tr>
<th></th>
<th>In Experiment (N=497)</th>
<th>Not in Experiment</th>
<th>Difference in SD units</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean [SD]</td>
<td>Mean [SD]</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Panel A. All Respondents Approached</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>33.3 [8.2]</td>
<td>35.3 [8.7]</td>
<td>-0.23***</td>
<td>8,887</td>
</tr>
<tr>
<td>Car driver</td>
<td>0.30 [0.46]</td>
<td>0.42 [0.49]</td>
<td>-0.25***</td>
<td>8,227</td>
</tr>
<tr>
<td>Log vehicle price (residual)</td>
<td>10.5 [0.4]</td>
<td>10.5 [0.4]</td>
<td>-0.00</td>
<td>7,200</td>
</tr>
<tr>
<td><strong>Panel B. Survey Respondents</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stated Daily Travel (Km/day)</td>
<td>47.0 [24.0]</td>
<td>45.1 [25.1]</td>
<td>0.08*</td>
<td>4,427</td>
</tr>
<tr>
<td>Stated Value of Time (Rs/hr)</td>
<td>216.6 [167.6]</td>
<td>193.0 [181.4]</td>
<td>0.13**</td>
<td>1,001</td>
</tr>
<tr>
<td>Stated Schedule Flexibility (min)</td>
<td>20.0 [10.9]</td>
<td>18.8 [12.0]</td>
<td>0.10*</td>
<td>952</td>
</tr>
</tbody>
</table>

- Experiment participants are younger. Car/motorcycle mostly driven by age.
  - No vehicle value difference after controlling for age & car
  - Similar occupation structure

### Experiment Participation
- Experiment participants are younger. Car/motorcycle mostly driven by age.
  - No vehicle value difference after controlling for age & car
  - Similar occupation structure
### Selection into Experiment

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<td>0.10*</td>
</tr>
</tbody>
</table>

- Experiment participants are younger. Car/motorcycle mostly driven by age.
  - No vehicle value difference after controlling for age & car Regression
  - Similar occupation structure Occupations

- Experiment participants have higher stated value of time, lower schedule costs
  - Caveat: stated preferences not predictive of experimental response
Inattention to Treatment Status

- Phone survey to measure attention to experiment (N=209)

<table>
<thead>
<tr>
<th></th>
<th>(1) Fraction</th>
<th>(2) N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Charges are per-KM</td>
<td>61.8%</td>
<td>133</td>
</tr>
<tr>
<td>Rate fn of departure time</td>
<td>57.8%</td>
<td>133</td>
</tr>
<tr>
<td>Peak rate correct</td>
<td>55.1%</td>
<td>133</td>
</tr>
<tr>
<td>Two out of three correct</td>
<td>55.4%</td>
<td>133</td>
</tr>
<tr>
<td>Knows area location</td>
<td>66.9%</td>
<td>132</td>
</tr>
<tr>
<td>Daily charges correct (4/5)</td>
<td>56.4%</td>
<td>132</td>
</tr>
</tbody>
</table>
Departure Time: Low Attrition

- Outcome: Dropped out (no subsequent data)
- Diff-in-diff: treatment group 0.02 higher (p-val 0.20)
Departure Times in Control (AM)

- **Y axis:** number of trips in control

![Graph showing departure times in control (AM)](image)

- Departure Time (hours relative to peak)
- Control
- Mean
- DT Charges

- Peaks indicate increased number of trips in control.
Departure Times Shifted Later (PM)

Impact of DT Charges
95% CI
DT Rate
Departure Times in Control (PM)
Departure Time: Difference in Difference Specification

\[ Y_{it} = \gamma^I T_i^{Info} \times Post_t + \gamma^L T_i^{Low} \times Post_t + \gamma^H T_i^{High} \times Post_t + \mu_w(t) + \alpha_i + \varepsilon_{it} \]

- Commuter \( i \), day \( t \), week \( w(t) \) (\( Post_t = 1 \) during experiment)

- Outcomes:
  - Total daily “shadow” rate
    - Same peak rate (100) for all commuters
  - Number of trips per day (extensive margin)

- Alternate specifications:
  - Shadow charges (rate \( \times \) km)
  - *Trip* instead of *day* level
Area Difference in Difference Specification

\[ Y_{it} = \gamma Treated_{it} + \mu_{w(t)} + \alpha_i + \varepsilon_{it} \]

- Commuter \( i \), day \( t \), week \( w(t) \)
- Compare treated “late” (week=1) with treated “early” (week=4)
- Outcomes: total daily shadow rate, number of trips
  - Shadow rate = 100 if intersect area, 0 otherwise.
## Area: No Additional Effect from Shorter Detour

<table>
<thead>
<tr>
<th></th>
<th>(1) Shadow Charges</th>
<th>(2) Google (minutes)</th>
<th>(3) Beliefs (minutes)</th>
<th>(4) Shadow Charges</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treated × Short Detour</td>
<td>-20.6***</td>
<td>5.4***</td>
<td>14.4***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(7.4)</td>
<td>(0.3)</td>
<td>(2.0)</td>
<td></td>
</tr>
<tr>
<td>Treated × Long Detour</td>
<td>-24.0**</td>
<td>9.1***</td>
<td>15.6***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(12.1)</td>
<td>(0.5)</td>
<td>(1.7)</td>
<td></td>
</tr>
<tr>
<td>Detour (minutes) (Short)</td>
<td></td>
<td></td>
<td>-1.5**</td>
<td>(0.7)</td>
</tr>
<tr>
<td>Detour (minutes) (Long)</td>
<td></td>
<td></td>
<td>-2.7**</td>
<td>(1.3)</td>
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<td>Observations</td>
<td>5,358</td>
<td>67</td>
<td>67</td>
<td>2,538</td>
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<tr>
<td>Control Mean</td>
<td>111.7</td>
<td>67</td>
<td>67</td>
<td>67</td>
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<tr>
<td>P-val Short=Long</td>
<td>0.82</td>
<td>0.00</td>
<td>0.64</td>
<td>0.42</td>
</tr>
</tbody>
</table>

- **Sub-treatment:** randomly induced longer detour (across commuters)
- **No “first-stage”** on participant beliefs of the detour
Area: No Additional Effect from Higher Area Charge

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>Shadow Charges</td>
<td>Beliefs (Rs.)</td>
<td>Shadow Charges</td>
</tr>
<tr>
<td>Treated × High Rate</td>
<td>-26.8*** (7.9)</td>
<td>191.6*** (3.3)</td>
<td></td>
</tr>
<tr>
<td>Treated × Low Rate</td>
<td>-20.1** (7.8)</td>
<td>101.8*** (3.2)</td>
<td></td>
</tr>
<tr>
<td>Rate (100 Rs.) (High)</td>
<td></td>
<td>-17.3*** (5.5)</td>
<td></td>
</tr>
<tr>
<td>Rate (100 Rs.) (Low)</td>
<td></td>
<td>-46.4*** (13.9)</td>
<td></td>
</tr>
</tbody>
</table>

- Observations: 8,827, 99, 3,838
- Commuters: 243, 99, 99
- Control Mean: 110.2
- P-val High=Low: 0.55, 0.00, 0.05

- Sub-treatment: low/high rate (across commuters)
Reduced Form Response Heterogeneity

- Significant overall heterogeneity:
  - Nearly bi-modal response distributions
  - Both departure time and area treatments

- Suggestive observed heterogeneity:
  - Regular commuters, self-employed, more expensive vehicles, older
### Observable Heterogeneity

<table>
<thead>
<tr>
<th>Dummy Variable $K$</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Regular</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Destination</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Self Employed</strong></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td><strong>Cheap Vehicle</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Older</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Small Stated $\alpha$</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Small Stated $\beta$</strong></td>
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</tbody>
</table>

#### Panel A. Departure Time: Trip Shadow Rate

<table>
<thead>
<tr>
<th>Charges $\times$ Post $\times (K = 0)$</th>
<th>-1.25</th>
<th>-2.74**</th>
<th>-5.81***</th>
<th>-1.06</th>
<th>-3.41**</th>
<th>-5.04***</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(2.17)</td>
<td>(1.30)</td>
<td>(1.63)</td>
<td>(1.90)</td>
<td>(1.52)</td>
<td>(1.92)</td>
</tr>
<tr>
<td>Charges $\times$ Post $\times (K = 1)$</td>
<td>-4.11***</td>
<td>-7.01***</td>
<td>-0.85</td>
<td>-4.70***</td>
<td>-4.26**</td>
<td>-2.68</td>
</tr>
<tr>
<td></td>
<td>(1.37)</td>
<td>(2.68)</td>
<td>(1.59)</td>
<td>(1.47)</td>
<td>(1.96)</td>
<td>(1.66)</td>
</tr>
</tbody>
</table>

- Observations: 43,776, 43,170, 43,776, 43,776, 40,783, 39,639
- P-value interaction: 0.27, 0.15, 0.03, 0.13, 0.73, 0.35

#### Panel B. Area: Trip Shadow Rate

<table>
<thead>
<tr>
<th>Treated $\times (K = 0)$</th>
<th>-11.91***</th>
<th>-11.29***</th>
<th>-7.04**</th>
<th>-12.92***</th>
<th>-9.65**</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(2.49)</td>
<td>(2.80)</td>
<td>(3.56)</td>
<td>(2.97)</td>
<td>(4.04)</td>
</tr>
<tr>
<td>Treated $\times (K = 1)$</td>
<td>-7.94**</td>
<td>-12.54***</td>
<td>-14.18***</td>
<td>-10.19***</td>
<td>-13.07***</td>
</tr>
<tr>
<td></td>
<td>(3.58)</td>
<td>(3.38)</td>
<td>(2.66)</td>
<td>(3.36)</td>
<td>(2.73)</td>
</tr>
</tbody>
</table>

- Observations: 20,367, 20,594, 20,594, 18,741, 18,260
- P-value interaction: 0.36, 0.78, 0.11, 0.54, 0.48
Departure Time Response Heterogeneity (AM)

- Individual Change in Shadow Charges (Post – Pre)
- Sample: regular commuters, AM trips before peak

Go Back
Area Response Heterogeneity (AM)

- Individual Fraction of Days Taking Short Route (Intersecting Area)
- Sample: regular commuters, AM trips on days visiting work
Departure Time: No Differential Data Quality

- **Outcome: Good Quality GPS Data:**
  - at most 3 hours effective missing data \( \left( \sum_i |gap_i - 0.75|_+ < 3 \right) \)
  - at most 2km jump without detailed route data

<table>
<thead>
<tr>
<th></th>
<th>(1) Good Quality Data</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>High Rate × Post</strong></td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
</tr>
<tr>
<td><strong>Low Rate × Post</strong></td>
<td>-0.01</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
</tr>
<tr>
<td><strong>Information × Post</strong></td>
<td>-0.01</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
</tr>
<tr>
<td><strong>Post</strong></td>
<td>0.09***</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
</tr>
<tr>
<td><strong>Commuter FE</strong></td>
<td>X</td>
</tr>
<tr>
<td><strong>Observations</strong></td>
<td>24,827</td>
</tr>
<tr>
<td><strong>Control Mean</strong></td>
<td>0.76</td>
</tr>
</tbody>
</table>
**Departure Time: Telephone Audit Results (pick-up)**

- **Outcome**: Respondent picks up telephone upon first attempt
- **Sample**: respondents who did not immediately drop out

<table>
<thead>
<tr>
<th></th>
<th>(1) Departure Time</th>
<th>(2) Area</th>
</tr>
</thead>
<tbody>
<tr>
<td>High Rate</td>
<td>0.01</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.15)</td>
<td></td>
</tr>
<tr>
<td>Low Rate</td>
<td>-0.24</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.16)</td>
<td></td>
</tr>
<tr>
<td>Information</td>
<td>0.04</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.10)</td>
<td></td>
</tr>
<tr>
<td>Area Treated</td>
<td></td>
<td>-0.07</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.20)</td>
</tr>
<tr>
<td>Strata FE</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Week FE</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Observations</td>
<td>108</td>
<td>73</td>
</tr>
<tr>
<td>Control Mean</td>
<td>0.74</td>
<td>0.65</td>
</tr>
</tbody>
</table>
Area: Slightly Better Data Quality in Treatment

- Outcome: Good Quality GPS Data:
  - at most 3 hours effective missing data \( \left( \sum_i |gap_i - 0.75|_+ < 3 \right) \)
  - at most 2km jump without detailed route data

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treated</td>
<td>0.05**</td>
<td>0.04</td>
<td>0.05**</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.03)</td>
<td>(0.02)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>Post</td>
<td>0.06*</td>
<td>0.06*</td>
<td>0.03</td>
<td>0.07**</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.03)</td>
<td>(0.03)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>Treated × High Rate</td>
<td>0.01</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treated × High Rate Day</td>
<td>-0.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treated × Short Detour</td>
<td></td>
<td></td>
<td>-0.05</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.05)</td>
<td></td>
</tr>
<tr>
<td>Commuter FE</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Observations</td>
<td>13,479</td>
<td>13,479</td>
<td>13,479</td>
<td>8,032</td>
</tr>
<tr>
<td>Control Mean</td>
<td>0.73</td>
<td>0.73</td>
<td>0.73</td>
<td>0.76</td>
</tr>
<tr>
<td></td>
<td>(1) Total Shadow Rates Today</td>
<td>(2)</td>
<td>(3)</td>
<td>(4) Number of Trips Today</td>
</tr>
<tr>
<td>----------------------</td>
<td>-----------------------------</td>
<td>-----</td>
<td>-----</td>
<td>---------------------------</td>
</tr>
<tr>
<td><strong>High Rate × Post</strong></td>
<td>-13.91**</td>
<td>-7.79**</td>
<td>-6.12*</td>
<td>-0.11</td>
</tr>
<tr>
<td></td>
<td>(6.08)</td>
<td>(3.80)</td>
<td>(3.40)</td>
<td>(0.14)</td>
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<tr>
<td><strong>Low Rate × Post</strong></td>
<td>-7.38</td>
<td>-2.76</td>
<td>-4.62</td>
<td>-0.06</td>
</tr>
<tr>
<td></td>
<td>(6.26)</td>
<td>(3.68)</td>
<td>(3.82)</td>
<td>(0.14)</td>
</tr>
<tr>
<td><strong>Information × Post</strong></td>
<td>-0.25</td>
<td>-0.25</td>
<td>-0.01</td>
<td>0.08</td>
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<tr>
<td></td>
<td>(5.39)</td>
<td>(3.27)</td>
<td>(3.30)</td>
<td>(0.13)</td>
</tr>
<tr>
<td><strong>Post</strong></td>
<td>1.12</td>
<td>-0.94</td>
<td>2.06</td>
<td>0.04</td>
</tr>
<tr>
<td></td>
<td>(4.92)</td>
<td>(2.89)</td>
<td>(3.08)</td>
<td>(0.11)</td>
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<tr>
<td><strong>Time of Day</strong></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Observations</td>
<td>15,610</td>
<td>15,610</td>
<td>15,610</td>
<td>15,610</td>
</tr>
<tr>
<td>Control Mean</td>
<td>96.54</td>
<td>48.30</td>
<td>48.24</td>
<td>3.05</td>
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### Departure Time: By Week in Study

<table>
<thead>
<tr>
<th>Sample:</th>
<th>Shadow Rates Today</th>
<th>Number of Trips Today</th>
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<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Week 1</td>
<td>Week 2</td>
<td>Week 3</td>
</tr>
<tr>
<td>High Rate × Post</td>
<td>-10.46</td>
<td>-16.07**</td>
</tr>
<tr>
<td></td>
<td>(7.41)</td>
<td>(7.76)</td>
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<td>Low Rate × Post</td>
<td>-8.32</td>
<td>-5.53</td>
</tr>
<tr>
<td></td>
<td>(7.61)</td>
<td>(8.15)</td>
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<td>Information × Post</td>
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<td>-2.11</td>
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<td>(6.45)</td>
<td>(6.73)</td>
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<td>Observations</td>
<td>11,925</td>
<td>11,895</td>
</tr>
<tr>
<td>Control Mean</td>
<td>95.87</td>
<td>96.75</td>
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</table>
## Area sub-treatments on number of trips

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<th>(3)</th>
<th>(4)</th>
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<tr>
<td><strong>Number of Trips Today</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treated</td>
<td>0.17**</td>
<td>0.09</td>
<td>0.24**</td>
<td>0.19</td>
</tr>
<tr>
<td></td>
<td>(0.08)</td>
<td>(0.09)</td>
<td>(0.10)</td>
<td>(0.13)</td>
</tr>
<tr>
<td>Treated × High Rate Day</td>
<td>0.17</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.14)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treated × High Rate</td>
<td></td>
<td>-0.16*</td>
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</tr>
<tr>
<td></td>
<td></td>
<td>(0.10)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treated × Short Detour</td>
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<td></td>
<td></td>
<td>-0.07</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.16)</td>
</tr>
<tr>
<td>Commuter FE</td>
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<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Day in Study FE</td>
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<td></td>
</tr>
<tr>
<td>Observations</td>
<td>8,878</td>
<td>8,878</td>
<td>8,878</td>
<td>5,417</td>
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<tr>
<td>Control Mean</td>
<td>2.50</td>
<td>2.50</td>
<td>2.50</td>
<td>2.53</td>
</tr>
</tbody>
</table>

- Impact on number of trips not robust.
Nested Logit: Routes and Departure Times

\[ u_i(h_D, j, h_{Ait}^*) = -\alpha_i T_{it}(h_D, j) \]
\[ -\beta_{Ei}|h_D + T_{it} - h_{Ait}^*| - \beta_{Li}|h_D + T_{it} - h_{Ait}^*| + \]
\[ \text{time early} \]
\[ \text{time late} \]
\[ + m_{it}(h_D, j) + \varepsilon_{it}(h_D, j) \]

- Nested logit, random utility shocks \( \varepsilon_{it}(h_D, j) \)
- Choice Probabilities
  - Upper nest: short route \( j = 0 \) vs detour route \( j = 1 \)
  - Lower nest: departure time \( h_D \) (5 minute bins)
Nested Logit: Routes and Departure Times

\[ u_i(h_D, j, h_{Ait}^*) = -\alpha_i T_{it}(h_D, j) \]

\[-\beta_{Ei}|h_D + T_{it} - h_{Ait}^*| - \beta_{Li}|h_D + T_{it} - h_{Ait}^*| + \]

\[ + m_{it}(h_D, j) + \varepsilon_{it}(h_D, j) \]

- Nested logit, random utility shocks \( \varepsilon_{it}(h_D, j) \)

- Upper nest: short route \( j = 0 \) vs detour route \( j = 1 \)
- Lower nest: departure time \( h_D \) (5 minute bins)
Nested Logit: Routes and Departure Times

\[ u_i(h_D, j, h^*_{Ait}) = -\alpha_i T_{it}(h_D, j) \]
\[ -\beta_{Ei}\left| h_D + T_{it} - h^*_{Ait}\right| - \beta_{Li}\left| h_D + T_{it} - h^*_{Ait}\right| + \]
\[ \text{time early} \quad \text{time late} \]
\[ + m_{it}(h_D, j) + \varepsilon_{it}(h_D, j) \]

- Nested logit, random utility shocks \( \varepsilon_{it}(h_D, j) \)
- Upper nest: short route \( j = 0 \) vs detour route \( j = 1 \)
- Lower nest: departure time \( h_D \) (5 minute bins)

- Congestion charges \( m_{it}^{DT}(h_D) + m_{it}^{A}(j) \)
Nested Logit: Routes and Departure Times

\[ u_i(h_D, j, h_{Ait}) = -\alpha_i T_{it}(h_D, j) - \beta_{Ei} | h_D + T_{it} - h_{Ait} | - \beta_{Li} | h_D + T_{it} - h_{Ait} | + \]
\[ m_{it}(h_D, j) + \varepsilon_{it}(h_D, j) \]

- Nested logit, random utility shocks \( \varepsilon_{it}(h_D, j) \)
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  - Lower nest: departure time \( h_D \) (5 minute bins)

- Congestion charges \( m_{it}^{DT}(h_D) + m_{it}^{A}(j) \)

- \( \alpha, \beta_E, \beta_L \) and discrete heterogeneity (e.g. inattention)

1. Respond to congestion charges with probability \( p \)
2. Ignore charges with probability \( 1 - p \)
Data and Estimation

- Commuter-specific choice set data:
  - Google Maps travel times for alternate dep time $h_D$ and route $j$
  - Log normal travel time distribution
  - Beliefs

Sample: 308 commuters with stable work location
Simulation: given $\alpha$, $\beta_E$, $\beta_L$, $h^*_A$, $A_i$, $T_i$, compute choice probabilities

Complication: invert unobserved distribution of ideal arrival $h^*_A$
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- Two-step GMM
Estimate Model using Experimental Variation

• Use experiment variation to estimate key preference params:
  ▶ Value of time driving \((\alpha)\)
  ▶ Schedule costs \((\beta_E, \beta_L)\)
Estimate Model using Experimental Variation

- Use experiment variation to estimate key preference params:
  - Value of time driving ($\alpha$)
  - Schedule costs ($\beta_E, \beta_L$)

- Discrete choice model over routes and departure times

  - Nested logit: route $j \in \{0, 1\}$ and $h_D$ in discrete grid
  - Discrete heterogeneity: attentive with probability $p$
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Estimation:

- Individual choice set (Google Maps travel times & uncertainty)
- GMM with moments that exploit experiment variation
## Results AM: Value of Time High vs. Early Arrival Cost

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- High value of time (4x in-sample hourly wage)
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  - Also consistent with fixed cost of switching

Discussion

Early arrival cost $\beta_E$ low relative to value of time $\alpha$

- Commuters have a moderate ability to adjust to congestion

- Probability to respond $\hat{p}$ similar to fraction attentive

Inattention
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Moments match experimental variation

All moments: in control and treatment

**Departure time:**
- Departure time shares $\Rightarrow \beta_E, \beta_L, \sigma$
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  - Variance in individual change in shadow charges
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- Departure time heterogeneity $\Rightarrow p$ (heterogeneity)
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**Route choice:**
- Short/long route shares $\Rightarrow \alpha, \mu$
- Route choice heterogeneity $\Rightarrow p$ (heterogeneity)
  - Distribution of individual short route choice frequency
Nested Logit Choice Probabilities

- Departure Time conditional on route $j$:
  \[
  \Pr (h_D \mid j, h^*_A) = \frac{\exp \left( V_i (h_D, j, h^*_A) / \sigma \right)}{\sum_h \exp \left( V_i (h, j, h^*_A) / \sigma \right)}
  \]

- Denote $LS_j = \log \left( \sigma \sum_h \exp \left( V_i (h, j, h^*_A) / \sigma \right) \right)$

- Route choice:
  \[
  \Pr (j \mid h^*_A) = \frac{\exp \left( LS_j / \mu \right)}{\exp \left( LS_0 / \mu \right) + \exp \left( LS_1 / \mu \right)}
  \]

- Nested logit restriction $\mu \geq \sigma$. 


Go Back
Discrete heterogeneity captures inattention

- Candidate model with random coefficients:

\[
\alpha_i = \alpha + \alpha_X X_i + \nu_i
\]
\[
\beta_{Ei} = \beta_E + \beta_{EX} X_i + \eta_i
\]
\[
\beta_{Li} = \beta_L + \beta_{LX} X_i + \mu_i
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  1. Respond to congestion charges, with probability \( p \)
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- Homogeneous preferences conditional on response:
  - \( \alpha_i = \alpha, \beta_{Ei} = \beta_E \) and \( \beta_{Li} = \beta_L \)
Beliefs: Changes in Travel Time Overestimated

<table>
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<tr>
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<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Trip Duration (belief)</td>
<td>Delta duration leaving earlier (belief)</td>
<td></td>
</tr>
<tr>
<td>Trip Duration (Google Maps)</td>
<td>0.70***</td>
<td>0.70***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.09)</td>
<td>(0.12)</td>
<td></td>
</tr>
<tr>
<td>Trip Distance (Google Maps)</td>
<td>0.02</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.21)</td>
<td></td>
<td></td>
</tr>
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<td></td>
<td>1.56***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.34)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>16.20***</td>
<td>16.23***</td>
<td>-2.75***</td>
</tr>
<tr>
<td></td>
<td>(3.20)</td>
<td>(3.23)</td>
<td>(0.80)</td>
</tr>
<tr>
<td>Observations</td>
<td>261</td>
<td>261</td>
<td>261</td>
</tr>
</tbody>
</table>

- Google Maps underestimates beliefs on travel time changes
- Consistent results for area treatment detours:
  - Average detour 6.5 minutes (Google Maps)
  - Average detour 13.6 minutes (phone survey stated beliefs)
Log Normal Travel Time (Route×Dep. Time Level)

- Log of normalized residual variation (across 146 weekdays)
- Distributed \( \approx \) log-normal (heavy tailed)
- \( T(h_D) \sim \log N(\mu(h_D), \sigma(h_D)) \)
Observation = route \times \text{departure time}. Computed over 146 weekdays

\[ T(h_D) \sim \log N(\mu(h_D), \sigma(h_D)) \]
Value of Time Discussion

- Transportation literature conventional estimate \( VOT = \text{half of wage} \)
  - Stated preferences (Small '12)
  - Hedonic regressions Ommeren and Fosgerau (2008)

- Revealed preference > stated preferences (Small et al '05)

- WTA higher than WTP (De Borger and Fosgerau '08, Hess et al. '08)
  - Here measuring WTA for extra time spent commuting

- Google Time lower variance compared to commuter beliefs
  - commuters believed detour twice as long as Google Maps
Structural Estimation Robustness

- Good model fit, including heterogeneity
- Bounds on late arrival cost $\beta_L$ (objective function flat $\beta_L \geq \bar{\beta}_L$)
- Model identification:
  - Sensitivity measure (Andrews et al '17)
  - Numerical check of identification using simulated data
Model Fit – Departure Times

- Good heterogeneity fit (variance in individual changes)

(A) Departure Time Market Shares

(B) Heterogeneity
Model Fit – Route Choice

- Good heterogeneity fit (inverse shape in treatment)

(A) Control

(B) Treatment
Expected utility with logit shocks:

$$Eu_i = \sigma \log \sum_h \exp \left( \frac{u_i(h_D) - t_i(h)}{\sigma} \right) + \sum_h \pi_i(h) t_i(h)$$
## Departure Time: Daily Shadow Rates Decrease

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<tr>
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<td>-14.32** ($7.23$)</td>
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<tr>
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<td>Information $\times$ Post</td>
<td>-1.44 ($6.44$)</td>
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<tr>
<td>Post only</td>
<td>X</td>
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</tr>
<tr>
<td>Commuter FE</td>
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<td>5,599</td>
<td>15,610</td>
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- No differential attrition
- Data Quality: Drop out at end < 10%
- Similar results AM/PM
- Effects start during second week

**Specification**
## Departure Time: Daily Shadow Rates Decrease

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Road Technology: Robustness

- Measuring speed. Robust to:
  - Measuring speed with GPS data
  - Controlling for trip characteristics

- Measuring traffic volume:
  - Very fine prediction by artery and time of day

- Similar results with density, time lags specifications

- Comparison to other settings:
  - Different from transportation engineering (convex) (e.g. BPR)
  - Similar city-wide results in Bogotá
    - Akbar and Duranton '17
  - New evidence: no hypercongestion
    - Anderson and Davis '18, Yang et al '18
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Linear Externality Bottleneck Model

- Impossible to fit Bangalore data with single bottleneck model
  - Low capacity: queue increases monotonically throughout the day
  - High capacity: no delay until very late in the day

- Solution: “traffic light” model with $N$ consecutive bottlenecks with traffic lights

- Two assumptions predict a linear relationship:
  - traffic lights create queues even for low inflows (much below capacity)
  - each bottleneck is relatively high-capacity (queues do not spill between traffic light cycles)

- Intuition for linear delay: queues form behind each traffic light and dissipate during the green cycle
Very similar to Akbar and Duranton (2017)

- Concave part: time lags and/or survey data bias (Zhao et al 2015)
Road Technology at Artery Level

- 22 arteries with Google Maps travel time data (in both directions)
Traffic volume (GPS) predicts travel time profile (Google Maps)

- \( \text{Adj } R^2 = 60\% \) with time-of-day FE, artery FE, artery-specific slopes
MSC higher after peak-hour: pushing others towards the peak.
Inefficiency with other Preferences and Road Technology

Outcome: percentage improvement going from unpriced Nash to social optimum

- Other preferences do not change conclusion
- Preferences matter more with convex road technology
## Inefficiency with Preferences Heterogeneity

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<tr>
<th>Distribution</th>
<th>SD($\alpha_i$)/$\bar{\alpha}_i$</th>
<th>Corr($\alpha_i$, $\beta_i$)</th>
<th>Nash Welfare</th>
<th>% Inefficiency</th>
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<td>Binomial</td>
<td>0.33</td>
<td>1</td>
<td>-774.8</td>
<td>0.71%</td>
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<tr>
<td>Log-normal</td>
<td>0.44</td>
<td>1</td>
<td>-772.2</td>
<td>0.85%</td>
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<tr>
<td>Log-normal</td>
<td>0.44</td>
<td>0</td>
<td>-743.4</td>
<td>0.60%</td>
</tr>
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- Binomial $(\alpha_i^H, \beta_i^H) = (2\alpha_i^L, 2\beta_i^L)$ or continuous (log-normal) heterogeneity
- Moderate heterogeneity in $(\alpha_i, \beta_i)$ does not change conclusion
Flexibility Compensates for Bad Road Technology

- High schedule flexibility (low $\beta_E/\alpha$) diminishes the negative effect of convex road technology

Outcome: unpriced Nash equilibrium
Social Optimum: Notable Travel Time Benefit...

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... But Modest Welfare Gain

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- Schedule costs comparable to benefits (externality + value of time)
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Schedule costs comparable to benefits (externality + value of time)
Inefficiency with Extensive Margin Decision

- Extensive margin decision $X = \{0, 1\}$ based on nested logit with trip value $\delta$

$$u(X, h_D) = \begin{cases} 
\delta + u(h_D) + \varepsilon(h_D, 1) & \text{if } X = 1 \\
\varepsilon(h_D, 0) & \text{if } X = 0 
\end{cases}$$

<table>
<thead>
<tr>
<th>Value of trip (Rs.)</th>
<th>Trip Probability Nash</th>
<th>Probability Social Opt.</th>
<th>Improvement (% of Nash)</th>
</tr>
</thead>
<tbody>
<tr>
<td>800</td>
<td>0.06</td>
<td>0.06</td>
<td>0.0%</td>
</tr>
<tr>
<td>900</td>
<td>0.49</td>
<td>0.45</td>
<td>1.6%</td>
</tr>
<tr>
<td>1,000</td>
<td>0.94</td>
<td>0.73</td>
<td>6.2%</td>
</tr>
<tr>
<td>1,100</td>
<td>1.00</td>
<td>0.82</td>
<td>4.5%</td>
</tr>
<tr>
<td>1,200</td>
<td>1.00</td>
<td>0.89</td>
<td>2.7%</td>
</tr>
<tr>
<td>1,300</td>
<td>1.00</td>
<td>0.95</td>
<td>1.6%</td>
</tr>
</tbody>
</table>
Inefficiency with Extensive Margin Decision

- Trip value $\delta = 1,000$, welfare improvement 6.2%