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

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International Growth Centre

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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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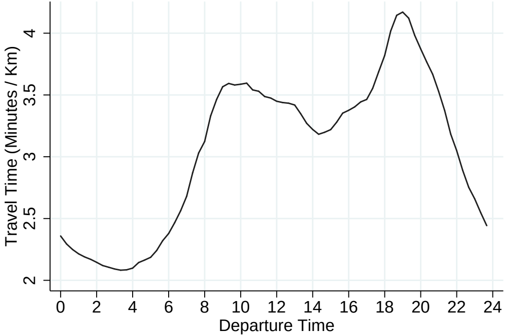
  - Theory solution: price externality, restore optimum (Pigou 1920, Vickrey 1969)
- Goal of this paper: how does social optimum look like in Bangalore?
  - Eliminate congestion completely?
  - Optimal to have some congestion? If so, how much?

This Paper: Peak-Hour Traffic Equilibrium



Source: Google Maps predicted travel times, 28 routes, Bangalore, India

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1. Peak-hours 1.5×-2× slower than nighttime

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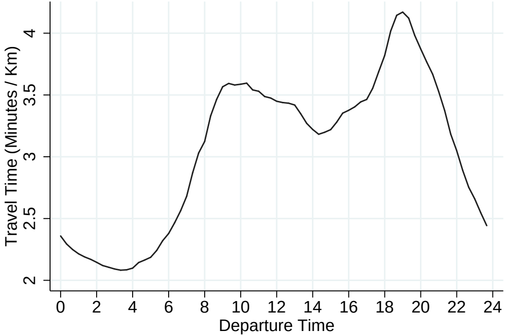

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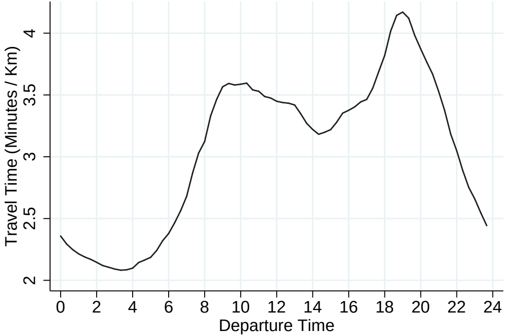

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3. Short-term responses relevant

This Paper: Quantify Peak-Hour Congestion Inefficiency

Research Questions:

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(4) Measure road traffic externality, and simulate the social optimum

Preview of Results

- Commuters respond to both policies:
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  - Commuters moderately schedule flexible
- However, moderate and linear externality
- 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

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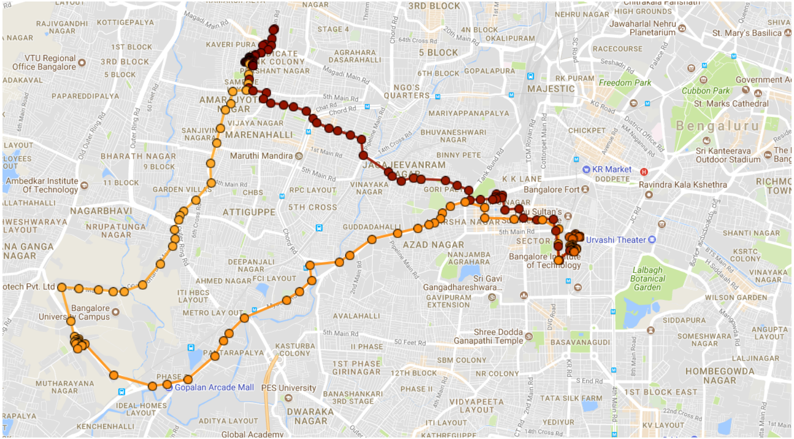
- Urban congestion literature:
  - Driving restrictions (Davis '08, Kreindler '16, Hanna, Kreindler, Olken '17)
  - Pollution (Hanna and Oliva '14, Gendron-Carrier et al '17)
  - Land use (Field '05, Harari '17)

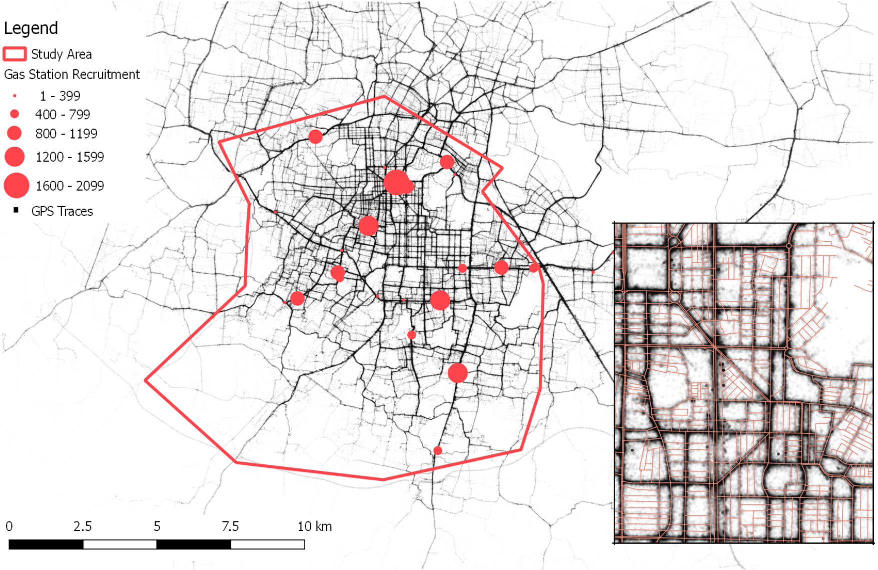
Plan of the Talk

Data: GPS Traces from Smartphone App

- Android app designed for this study + automatic GPS data processing Details



Sample: Study Area, Recruitment in Gas Stations



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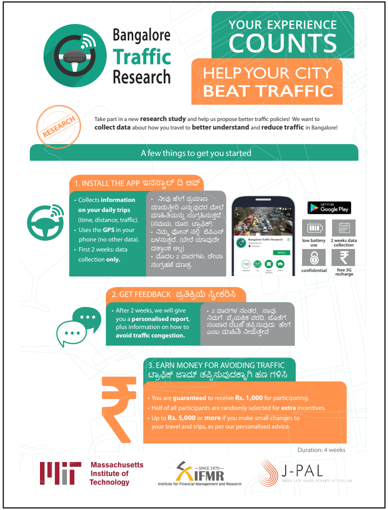
  - 2,300 installed app
  - 497 experiment participants Selection



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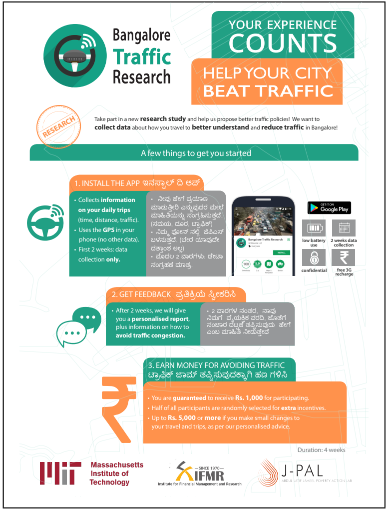

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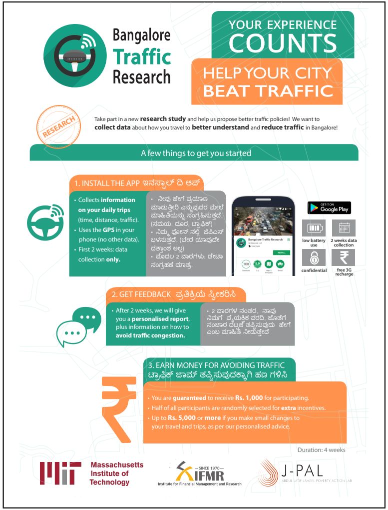
- Experimental platform
  - Charges deducted from initial grant
  - Weekly bank transfers
  - Daily SMS reports Stats



Utility over Travel Time and Scheduling Costs

$$u\left(h_D, T\right) = -\alpha T - \beta_E | \underbrace{h_D + T - h_A^*}_{\text{time early}} |_- - \beta_L | \underbrace{h_D + T - h_A^*}_{\text{time late}} |_+ + m$$

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

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- Components:
  - h_D departure time (decision variable)
  - $T = T(h_D)$ random travel time, realized after departure
  - m money (e.g. congestion charges)
- Preferences:
  - α: value of time commuting
  - Ideal arrival time h_A^* known before departure
  - β_E, β_L: cost of arriving early / late

Identifying α, β_E, β_L with Observational Data

$$u_i\left(h_{Dit}, h^*_{Ait}\right) = -\alpha T_{it} - \beta_E \left| \underbrace{h_{Dit} + T_{it} - h^*_{Ait}}_{\text{time early}} \right|_- - \beta_L \left| \underbrace{h_{Dit} + T_{it} - h^*_{Ait}}_{\text{time late}} \right|_+ + \varepsilon_{it}\left(h_{Dit}\right)$$

- Panel data on departure time h_{Dit}
- Observed "prices": travel time profile $T_{it}\left(h_D\right) \overset{iid}{\sim} \mathcal{T}_i\left(h_D\right)$
- Unobserved "prices": ideal arrival time distribution $h^*_{Ait} \overset{iid}{\sim} \mathcal{A}_i$

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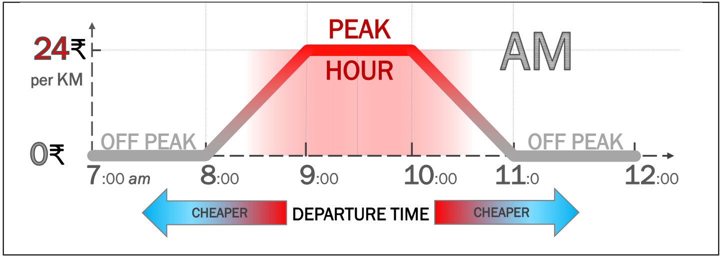
- Approach here: create experimental variation in price of h_D and price of T_{it}

Experiment: Peak-hour Departure Time Charge



- Each trip charged with per-kilometer (variable) rate

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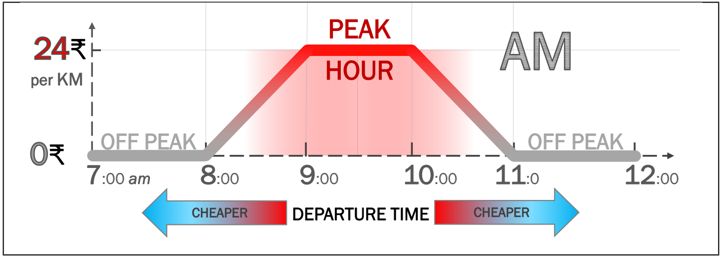
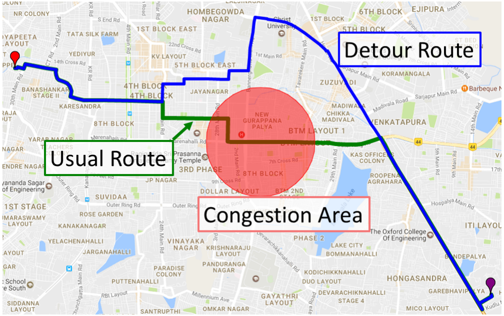


- Each trip charged with per-kilometer (variable) rate
- Sub-treatments:
  - low rate 12 $\mathrm{Rs/Km}$ ($\sim$ effective Uber per-km rate in Bangalore)
  - high rate 24 $\mathrm{Rs/Km}$ ($\sim$ 0.4\$)
  - information and nudge Info

Experiment: Congestion Area Flat Charge

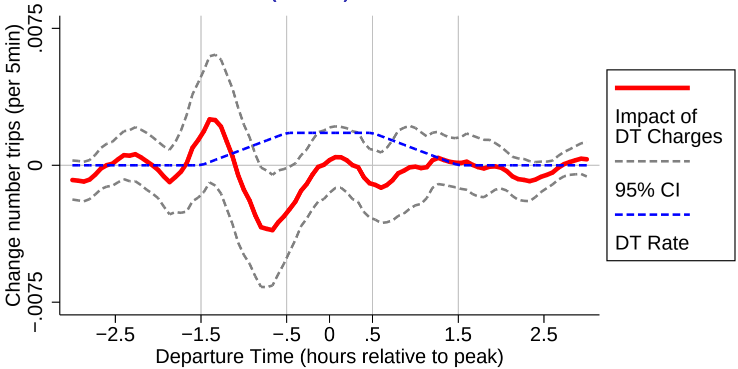


- Flat charge for crossing area. This induces a detour option (longer route, but free)
- Route choice informative about value of travel time
- Sub-treatments:
  - (A) low / high charge $p_A \in \{\text{Rs.}\,80, \text{Rs.}\,160\}$
  - (B) short / long detour $D \in [3, 14]$ minutes

In Person Meeting to Explain Treatment

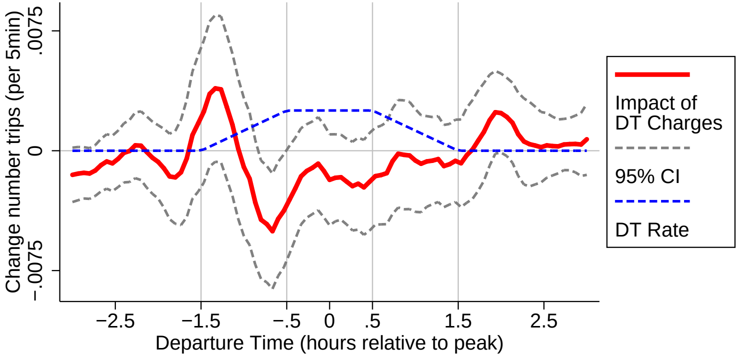
Randomization

Departure Times Shift Earlier (AM)



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

Departure Times Shift Earlier (AM)



- Sample: all morning trips, all respondents

Area: Daily Shadow Rates Decrease

	(1)	(2)
	Shadow Rates Today	
Treated	-22.82***	
	(5.53)	
Treated Week 1		-26.16***
		(8.30)
Treated Week 4		-19.18*
		(10.06)
Commuter FE	X	X
Observations	8,878	8,878
Control Mean	107.68	116.16

- Slightly higher GPS data quality in treatment group Data Quality
- Similar effects throughout treatment (days 1-5)

Specification
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Commuter FE	X	X	X	X
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Control Mean	107.68	116.16	2.50	2.56

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- Structurally estimate model of morning departure time decision
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- Results:
  - High value of time spent driving ($4\times$ in sample hourly wage)
  - Commuters moderately schedule flexible

Details

Results AM: Value of Time High vs. Early Arrival Cost

(1)	(2)	(3)	(4)	(5)
Value of time α (Rs/hr)	Schedule cost early β_E (Rs/hr)	Logit inner σ (dep. time.)	Logit outer μ (route)	Probability to respond p
1,121.9	319.4	36.5	36.9	0.46
(318.7)	(134.5)	(65.4)	(9.3)	(0.13)

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

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Measuring the Impact of Traffic Volume on Travel Time

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

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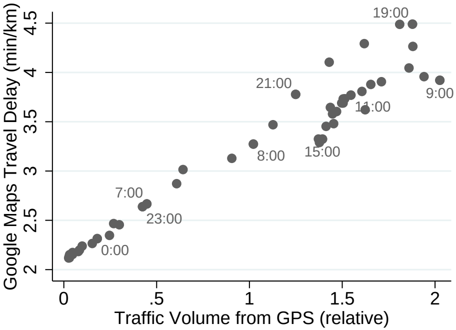
Moderate, Linear Impact of Traffic Volume on Travel Time



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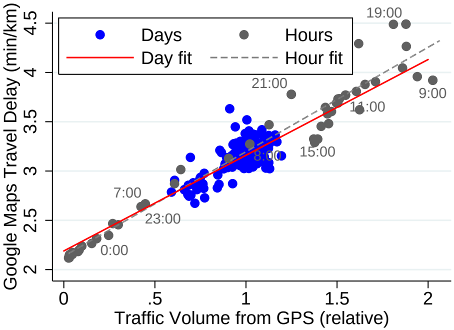

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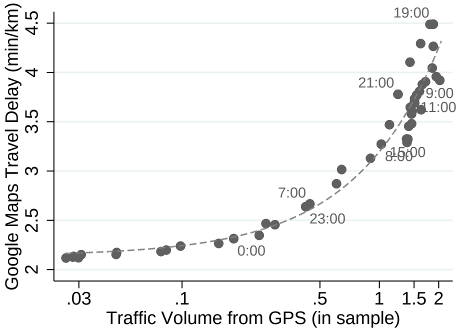

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- Couture et al (2018) find -0.13 elasticity of speed to tvehicle otal time travelled in US cities

Citywide Traffic Equilibrium

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

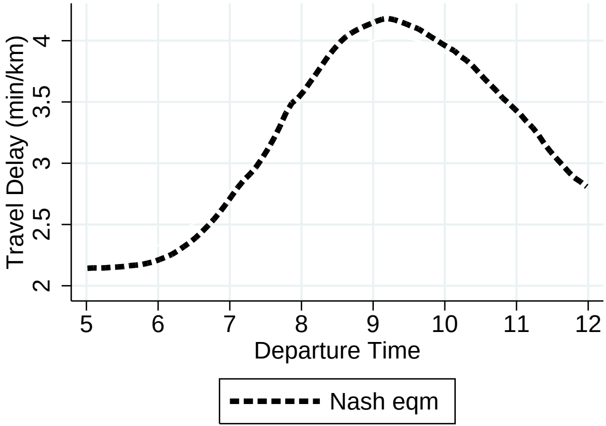
Two steps:

(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...



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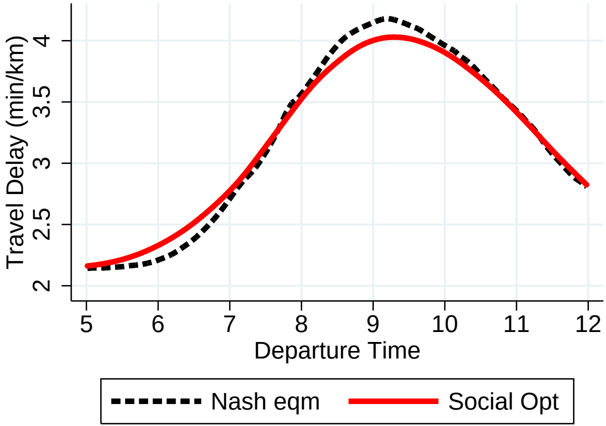

- "Best-case" social optimum: no implementation costs and all revenue redistributed lump-sum

Marginal Soc Cost

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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  - In this setting, the results driven by shape of externality.
- Similar results with other preferences, moderate heterogeneity, extensive margin.

Preferences, Externality, Heterogeneity, Extensive Margin

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

Other Preferences, Technology

Preferences, Externality, Heterogeneity, Extensive Margin

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Preference Heterogeneity

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- Convex road technology: higher travel time and welfare improvements

Other Preferences, Technology

- Moderate heterogeneity in (α_i, β_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

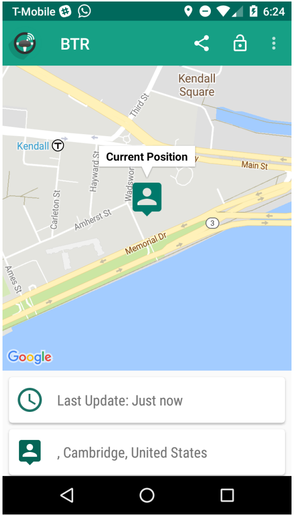
- Precisely targeted road pricing technology exists. Would it improve cities?
- In Bangalore, peak-hour pricing less attractive than believed
  - Severe congestion does not *automatically* imply pricing is attractive
- Other important margins:
  - pollution (generation & exposure)
  - public transit
  - firm demand for travel

Thank You!

Data: GPS Traces from Smartphone App

- Android app designed for this study
  - 76% smartphone owernship among sampling frame
  - App runs in background
- Automatic GPS data processing
  - identifying outliers
  - raw GPS $\rightarrow$ trips (start, end, route)
- Data coverage: 70–80% days

Back



Descriptive Statistics: Travel Behavior (GPS Data)

	Mean	Std. Dev.	Obs.
Panel A. Trip Characteristics			
Total Number of Trips			51,164
Number of Trips per Day	3.15	[1.16]	497
Median trip duration (minutes)	27.38	[12.77]	497
Median trip length (Km.)	7.2	[4.7]	497
Panel B. Commute Destination Variability			
Regular Commuter	0.76		497
Frac. of days present at Work	0.86		378
Frac. trips Home-Work or Work-Home	0.39		378
Panel C. Departure Time Variability (Std.Dev. in hours)			
First Trip (AM)	1.24	[0.50]	496
First Home to Work Trip (AM)	0.62	[0.52]	332

- Significant route and departure time heterogeneity Distributions

Study Eligibility

	N	%
Approached	10,537	100%
Own vehicle	9,893	94%
Drive $\geq$ 3 days/wk	9,203	87%
Drive $\geq$ 20 km/day	7,398	70%
In Bangalore	7,052	67%
Own GPS smartphone	5,372	51%

- Survey "Daily Km" three times higher than measured by GPS

Go Back

Selection into Experiment

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

Go Back

Selection into Experiment: Occupations

	(1) In the Experiment	(2) Not in the Experiment
Business owner or manager	16.7%	15.6%
Accountant, Teacher, Doctor	7.5%	6.3%
Software and IT	10.3%	10.1%
Engineers, Technical	14.3%	11.2%
Office staff	15.4%	18.1%
Manual jobs	8.4%	9.5%
Mobile professions	15.6%	12.0%
Student	9.0%	13.4%
Others, Retired	2.9%	3.9%
Total	455	2,464

Go Back

Travel Behavior (GPS App Data)

	(1) Median	(2) Mean	(3) Std. Dev.	(4) 10 Perc.	(5) 90 Perc.	(6) Obs.
Panel A. Trip Characteristics						
Total Number of Trips						51,164
Number of Trips per Day	2.85	3.15	[1.16]	1.90	4.85	497
Median trip duration (minutes)	24.50	27.38	[12.77]	15.05	42.60	497
Median trip length (Km.)	5.91	7.17	[4.66]	2.90	13.36	497
Panel B. Commute Destination Variability						
Regular Commuter		0.76				497
Frac. trips Home-Work, Work-Home	0.38	0.39	[0.21]	0.13	0.67	378
Frac. of trips Work-Work	0.03	0.06	[0.08]	0.00	0.15	378
Frac. of days present at Work	0.91	0.86	[0.16]	0.61	1.00	378
Panel C. Departure Time Variability						
(Standard Deviation of the Departure Time in hours)						
First Trip (AM)	1.27	1.24	[0.50]	0.52	1.85	496
Last Trip (PM)	1.72	1.71	[0.50]	1.06	2.34	497
First Home to Work Trip (AM)	0.48	0.62	[0.52]	0.15	1.28	332
Last Work to Home Trip (PM)	0.80	0.94	[0.62]	0.28	1.78	321

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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)

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  - **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

$$u(h_D, T) = -\alpha T - \beta_E | \underbrace{h_D + T - h_A^*}_{\text{time early}} |_- - \beta_L | \underbrace{h_D + T - h_A^*}_{\text{time late}} |_+ + m$$

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

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- Components:
  - h_D departure time (decision variable)
  - $T = T(h_D)$ random travel time, realized after departure
  - m money (e.g. congestion charges)
- Preferences:
  - α: value of time commuting
  - Ideal arrival time h_A^* known before departure
  - β_E, β_L: cost of arriving early / late

Graph Nonparametric Identification

Identifying α, β_E, β_L with Observational Data

$$u_i\left(h_D, h^*_{Ait}\right) = -\alpha T_{it} - \beta_E \left| \underbrace{h_D + T_{it} - h^*_{Ait}}_{\text{time early}} \right|_- - \beta_L \left| \underbrace{h_D + T_{it} - h^*_{Ait}}_{\text{time late}} \right|_+ + \varepsilon_{it}\left(h_D\right)$$

- Heterogeneity:
  - In principle can accommodate α_i, β_{Ei}, β_{Li}
  - $\varepsilon_{it}\left(h_D\right)$ extreme value distributed

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- Identification challenge with observational data: price endogeneity
  - Observed "prices": travel time profile $T_{it}\left(h_D\right) \overset{iid}{\sim} \mathcal{T}_i\left(h_D\right)$
  - Unobserved "prices": ideal arrival time distribution $h^*_{Ait} \overset{iid}{\sim} \mathcal{A}_i$

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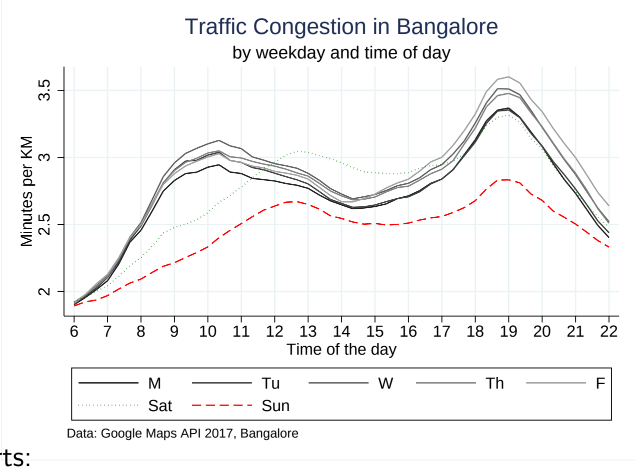
  - Unobserved "prices": ideal arrival time distribution $h^*_{Ait} \overset{iid}{\sim} \mathcal{A}_i$
- Approach here: create experimental variation in price of h_D and price of T_{it}

Departure Time Information Sub-Treatment



- 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

Back

Randomized Experiment Design

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

Back

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

Other Design Information

Deisgn 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 8×8 bipartite graph with 8 perfect matchings (randomly)
  - Solution: augmenting path algorithm to select matchings (König 1931)

Go Back

Experimental Design Matrix

	Week	Control		Information		Low Rate		High Rate	
Strata 1-4	1	AREA	control	AREA	info	AREA	low rate	AREA	high rate
	2	control	control	info	info	low rate	low rate	high rate	high rate
	3	control	control	info	info	low rate	low rate	high rate	high rate
	4	control	AREA	info	AREA	low rate	AREA	high rate	AREA
Strata 5-8	1	control	control	info	info	info	low rate	info	high rate
	2	control	control	info	info	low rate	low rate	high rate	high rate
	3	control	control	info	info	low rate	low rate	high rate	high rate
	4	control	control	info	info	low rate	info	high rate	info

Go Back

Selection into Experiment

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

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

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  - No vehicle value difference after controling 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)

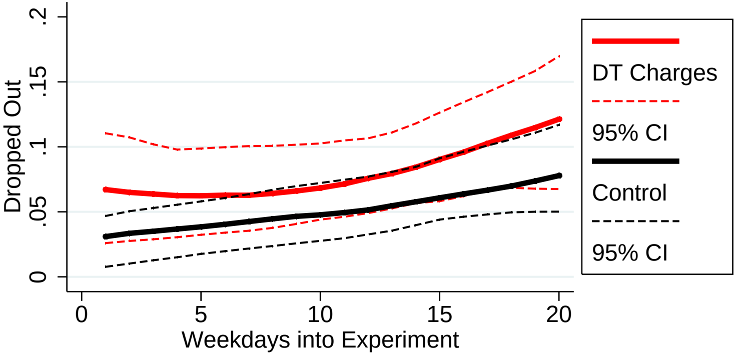
	(1) Fraction	(2) N
Charges are per-KM	61.8%	133
Rate fn of departure time	57.8%	133
Peak rate correct	55.1%	133
Two out of three correct	55.4%	133

	(1) Fraction	(2) N
Knows area location	66.9%	132
Daily charges correct (4/5)	56.4%	132

Go Back

Departure Time: Low Attrition

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



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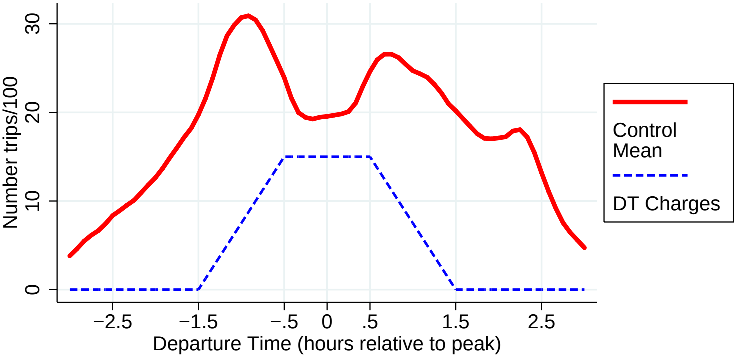
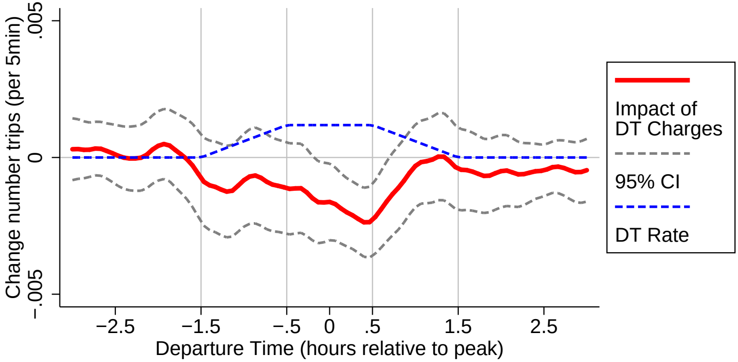
Departure Times in Control (AM)



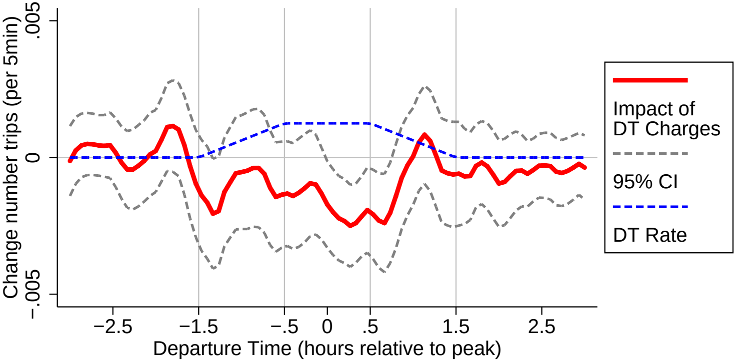
- Y axis: number of trips in control Go Back

Departure Times Shifted Later (PM)



Go Back

Departure Times in Control (PM)



Go Back

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

Go Back

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.

Go Back

Area: No Additional Effect from Shorter Detour

	(1) Shadow Charges	(2) Google (minutes)	(3) Beliefs (minutes)	(4) Shadow Charges
Treated × Short Detour	-20.6***	5.4***	14.4***	
	(7.4)	(0.3)	(2.0)	
Treated × Long Detour	-24.0**	9.1***	15.6***	
	(12.1)	(0.5)	(1.7)	
Detour (minutes) (Short)				-1.5**
				(0.7)
Detour (minutes) (Long)				-2.7**
				(1.3)
Observations	5,358	67	67	2,538
Commuters	148	67	67	67
Control Mean	111.7			
P-val Short=Long	0.82	0.00	0.64	0.42

- 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

	(1) Shadow Charges	(2) Beliefs (Rs.)	(3) Shadow Charges
Treated × High Rate	-26.8***	191.6***	
	(7.9)	(3.3)	
Treated × Low Rate	-20.1**	101.8***	
	(7.8)	(3.2)	
Rate (100 Rs.) (High)			-17.3***
			(5.5)
Rate (100 Rs.) (Low)			-46.4***
			(13.9)
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)

Back

Reduced Form Response Heterogeneity

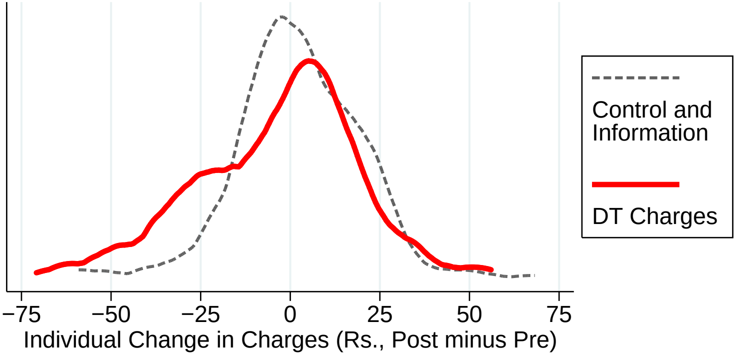
- Significant overall heterogeneity:
  - Nearly bi-modal response distributions
  - Both departure time and area treatments
  - Distributions
- Suggestive observed heterogeneity:
  - Regular commuters, self-employed, more *expensive* vehicles, older
  - Observed

Observable Heterogeneity

Heterogeneity Dummy Variable K	(1) Regular Destination	(2) Self Employed	(3) Cheap Vehicle	(4) Older	(5) Small Stated α	(6) Small Stated β
Panel A. *Departure Time: Trip Shadow Rate*						
Charges$\times$Post$\times$($K=0$)	-1.25	-2.74**	-5.81***	-1.06	-3.41**	-5.04***
	(2.17)	(1.30)	(1.63)	(1.90)	(1.52)	(1.92)
Charges$\times$Post$\times$($K=1$)	-4.11***	-7.01***	-0.85	-4.70***	-4.26**	-2.68
	(1.37)	(2.68)	(1.59)	(1.47)	(1.96)	(1.66)
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*						
Treated$\times$($K=0$)		-11.91***	-11.29***	-7.04**	-12.92***	-9.65**
		(2.49)	(2.80)	(3.56)	(2.97)	(4.04)
Treated$\times$($K=1$)		-7.94**	-12.54***	-14.18***	-10.19***	-13.07***
		(3.58)	(3.38)	(2.66)	(3.36)	(2.73)
Observations		20,367	20,594	20,594	18,741	18,260
P-value interaction		0.36	0.78	0.11	0.54	0.48

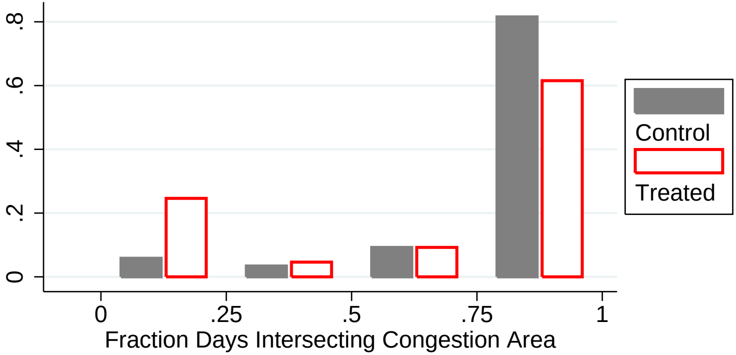
Go Back

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 Go Back

Departure Time: No Differential Data Quality

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

	(1) *Good Quality Data*
High Rate × Post	0.01
	(0.05)
Low Rate × Post	-0.01
	(0.05)
Information × Post	-0.01
	(0.04)
Post	0.09***
	(0.04)
Commuter FE	X
Observations	24,827
Control Mean	0.76

Go Back

Departure Time: Telephone Audit Results (pick-up)

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

	(1) Departure Time	(2) Area
High Rate	0.01	
	(0.15)	
Low Rate	-0.24	
	(0.16)	
Information	0.04	
	(0.10)	
Area Treated		-0.07
		(0.20)
Strata FE	X	X
Week FE	X	X
Observations	108	73
Control Mean	0.74	0.65

Go Back

Area: Sligthly Better Data Quality in Treatment

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

	(1)	(2)	(3)	(4)
		Good Quality Data		
Treated	0.05**	0.04	0.05**	0.05
	(0.02)	(0.03)	(0.02)	(0.03)
Post	0.06*	0.06*	0.03	0.07**
	(0.03)	(0.03)	(0.03)	(0.04)
Treated × High Rate		0.01		
		(0.04)		
Treated × High Rate Day			-0.00	
			(0.02)	
Treated × Short Detour				-0.05
				(0.05)
Commuter FE	X	X	X	X
Observations	13,479	13,479	13,479	8,032
Control Mean	0.73	0.73	0.73	0.76

Go Back

Departure Time: Similar Results AM/PM

	(1)	(2)	(3)	(4)	(5)	(6)
	Total Shadow Rates Today			Number of Trips Today		
High Rate × Post	-13.91**	-7.79**	-6.12*	-0.11	-0.04	-0.06
	(6.08)	(3.80)	(3.40)	(0.14)	(0.07)	(0.07)
Low Rate × Post	-7.38	-2.76	-4.62	-0.06	-0.00	-0.07
	(6.26)	(3.68)	(3.82)	(0.14)	(0.07)	(0.07)
Information × Post	-0.25	-0.25	-0.01	0.08	0.05	0.03
	(5.39)	(3.27)	(3.30)	(0.13)	(0.06)	(0.07)
Post	1.12	-0.94	2.06	0.04	-0.01	0.06
	(4.92)	(2.89)	(3.08)	(0.11)	(0.06)	(0.06)
Time of Day		AM	PM		AM	PM
Observations	15,610	15,610	15,610	15,610	15,610	15,610
Control Mean	96.54	48.30	48.24	3.05	1.16	1.30

Go Back

Departure Time: By Week in Study

	(1)	(2)	(3)	(4)	(5)	(6)
	Shadow Rates Today			Number of Trips Today		
Sample:	Week 1	Week 2	Week 3	Week 1	Week 2	Week 3
High Rate × Post	-10.46	-16.07**	-15.26*	-0.10	-0.09	-0.13
	(7.41)	(7.76)	(7.87)	(0.17)	(0.18)	(0.18)
Low Rate × Post	-8.32	-5.53	-5.30	-0.17	0.19	-0.09
	(7.61)	(8.15)	(7.84)	(0.17)	(0.18)	(0.18)
Information × Post	-2.93	-2.11	4.16	-0.05	0.11	0.19
	(6.45)	(6.73)	(7.21)	(0.15)	(0.16)	(0.17)
Observations	11,925	11,895	11,812	11,925	11,895	11,812
Control Mean	95.87	96.75	94.09	2.93	2.96	2.95

Go Back

Area sub-treatments on number of trips

	(1)	(2)	(3)	(4)
	Number of Trips Today			
Treated	0.17**	0.09	0.24**	0.19
	(0.08)	(0.09)	(0.10)	(0.13)
Treated × High Rate		0.17		
		(0.14)		
Treated × High Rate Day			-0.16*	
			(0.10)	
Treated × Short Detour				-0.07
				(0.16)
Commuter FE	X	X	X	X
Day in Study FE			X	
Observations	8,878	8,878	8,878	5,417
Control Mean	2.50	2.50	2.50	2.53

- Impact on number of trips not robust.

Go Back

Nested Logit: Routes and Departure Times

$$
\begin{aligned}
u_i\left(h_D, j, h^*_{Ait}\right) = & -\alpha_i T_{it}(h_D, j) \\
& -\beta_{Ei} | \underbrace{h_D + T_{it} - h^*_{Ait}}_{\text{time early}} |_{-} - \beta_{Li} | \underbrace{h_D + T_{it} - h^*_{Ait}}_{\text{time late}} |_{+} \\
& + m_{it}\left(h_D, j\right) + \varepsilon_{it}\left(h_D, j\right)
\end{aligned}
$$

- 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)

Back

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Back

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- Congestion charges $m^{DT}_{it}\left(h_D\right) + m^A_{it}(j)$
- α, β_E, β_L and *discrete* heterogeneity (e.g. inattention) Details
  (1) Respond to congestion charges with probability p
  (2) Ignore charges with probability $1 - p$

Back

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 Log Normal and Std.Dev.
  - Beliefs Beliefs Travel Time

Back

Data and Estimation

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  - Google Maps travel times for alternate dep time h_D and route j
  - Log normal travel time distribution Log Normal and Std.Dev.
  - Beliefs Beliefs Travel Time
- Sample: 308 commuters with stable work location
- Simulation: given α, β_E, β_L, h^*_{Ait}, $\mathcal{T}_i$, compute choice probabilities
  - Complication: invert unobserved distribution of ideal arrival h^*_{Ait}
- Two-step GMM

Back

Estimate Model using Experimental Variation

- Use experiment variation to estimate key preference params:
  - Value of time driving (α)
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Estimation: Estimation

- Individual choice set (Google Maps travel times & uncertainty)
- GMM with moments that exploit experiment variation Moments

Results AM: Value of Time High vs. Early Arrival Cost

(1)	(2)	(3)	(4)	(5)
Value of time α (Rs/hr)	Schedule cost early β_E (Rs/hr)	Logit inner σ (dep. time.)	Logit outer μ (route)	Probability to respond p
1,121.9	319.4	36.5	36.9	0.46
(318.7)	(134.5)	(65.4)	(9.3)	(0.13)

- High value of time (4x in-sample hourly wage)
  - Identified from detour vs charge (not from pure price variation)
  - Also consistent with fixed cost of switching Discussion

Robustness and Fit
Back

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Robustness and Fit
Back

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

Robustness and Fit
Back

Moments match experimental variation

All moments: in control and treatment

Departure time:

- Departure time shares $\Rightarrow \beta_E, \beta_L, \sigma$

Back

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  - Variance in individual change in shadow charges

Back

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Route choice:

- Short/long route shares $\Rightarrow \alpha, \mu$

Back

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- Departure time heterogeneity $\Rightarrow p$ (heterogeneity)
  - Variance in individual change in shadow charges

Route choice:

- Short/long route shares $\Rightarrow \alpha, \mu$
- Route choice heterogeneity $\Rightarrow p$ (heterogeneity)
  - Distribution of individual short route choice frequency

Back

Nested Logit Choice Probabilities

- Departure Time conditional on route j:

$$\Pr\left(h_D \mid j, h_A^*\right) = \frac{\exp\left(V_i\left(h_D, j, h_A^*\right)/\sigma\right)}{\sum_h \exp\left(V_i\left(h, j, h_A^*\right)/\sigma\right)}$$

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

$$\Pr\left(j \mid h_A^*\right) = \frac{\exp\left(LS_j/\mu\right)}{\exp\left(LS_0/\mu\right) + \exp\left(LS_1/\mu\right)}$$

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

Go Back

Discrete heterogeneity captures inattention

- Candidate model with random coefficients:

$$\alpha_i = \alpha + \alpha_X X_i + \nu_i$$
$$\beta_{Ei} = \beta_E + \beta_{EX} X_i + \eta_i$$
$$\beta_{Li} = \beta_L + \beta_{LX} X_i + \mu_i$$

◂ Go Back

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Go Back

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Go Back

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- Better fit: *discrete* heterogeneity (e.g. inattention, or inflexible)
  (1) Respond to congestion charges, with probability p
  (2) Ignore charges with probability $1 - p$
- Homogeneous preferences conditional on response:
  - $\alpha_i = \alpha$, $\beta_{Ei} = \beta_E$ and $\beta_{Li} = \beta_L$

Go Back

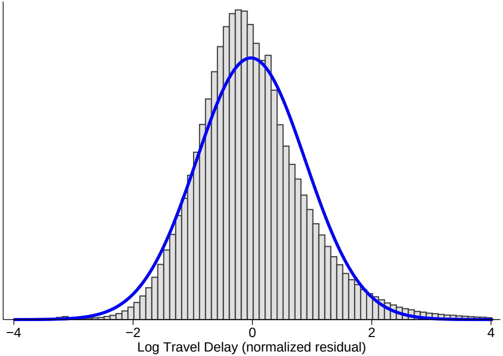
Beliefs: Changes in Travel Time Overestimated

	(1)	(2)	(3)
	Trip Duration (belief)		Δ duration leaving earlier (belief)
Trip Duration (Google Maps)	0.70***	0.70***	
	(0.09)	(0.12)	
Trip Distance (Google Maps)		0.02	
		(0.21)	
Δ duration leaving earlier (Google Maps)			1.56***
			(0.34)
Constant	16.20***	16.23***	-2.75***
	(3.20)	(3.23)	(0.80)
Observations	261	261	261

- 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)

Go Back

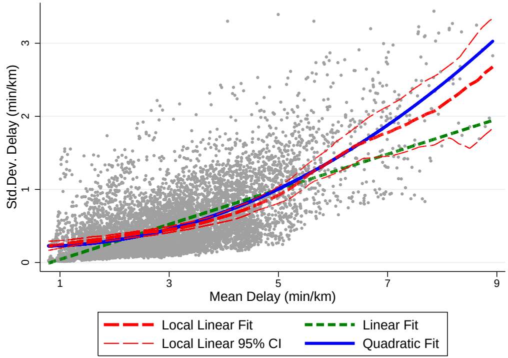
Log Normal Travel Time (Route×Dep. Time Level)



- Log of normalized residual variation (across 146 weekdays)
- Distributed ≈ log-normal (heavy tailed)
- $T\left(h_D\right) \sim \log N\left(\mu\left(h_D\right), \sigma\left(h_D\right)\right)$

Go Back

Uncertainty: Substantial Travel Time Variation



- Observation = route $\times$ departure time. Computed over 146 weekdays
- $T(h_D) \sim \log N(\mu(h_D), \sigma(h_D))$

Go Back

Value of Time Discussion

- Transportation literature conventional estimate VOT $=$ 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

Go Back

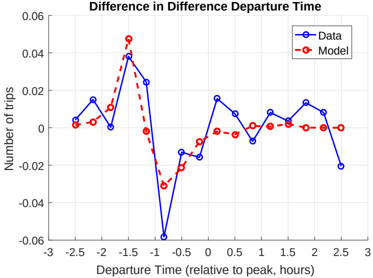
Structural Estimation Robustness

- Good model fit, including heterogeneity Heterogeneity Fit
- Bounds on late arrival cost β_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

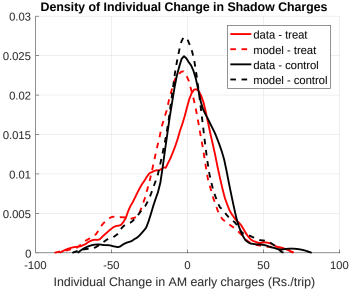
Back

Model Fit – Departure Times

- Good heterogeneity fit (variance in individual changes)



(A) Departure Time Market Shares

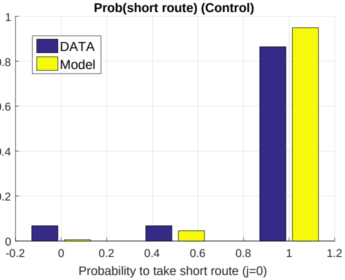


(B) Heterogeneity

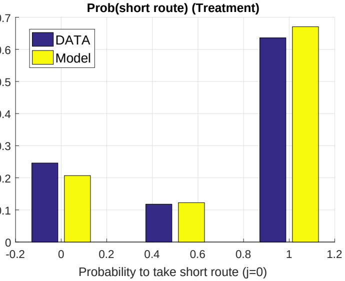
Back

Model Fit – Route Choice

- Good heterogeneity fit (inverse shape in treatment)



(A) Control



(B) Treatment

Back

Logit Expected Utility

Expected utility with logit shocks:

$$Eu_i = \sigma \log \sum_h \exp\left(\frac{u_i(h_D) - t_i(h)}{\sigma}\right) + \sum_h \pi_i(h)\, t_i(h)$$

◂ Go Back

Departure Time: Daily Shadow Rates Decrease

	(1)	(2)
	Shadow Rates Today	
High Rate × Post	-14.32**	-13.91**
	(7.23)	(6.08)
Low Rate × Post	-0.87	-7.38
	(7.20)	(6.26)
Information × Post	-1.44	-0.25
	(6.44)	(5.39)
Post only	X	
Commuter FE		X
Observations	5,599	15,610
Control Mean	96.54	96.54

- No differential attrition Data Quality Drop out at end $< 10\%$ Droped Out
- Similar results AM/PM Full Results
- Effects start during second week By week

Specification

Departure Time: Daily Shadow Rates Decrease

	(1)	(2)	(3)	(4)
	Shadow Rates Today		Trips Today	
High Rate × Post	-14.32**	-13.91**	-0.19	-0.11
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Post only	X		X	
Commuter FE		X		X
Observations	5,599	15,610	5,599	15,610
Control Mean	96.54	96.54	3.05	3.05

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Specification

Road Technology: Robustness

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

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- Measuring speed. Robust to:
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- Measuring traffic volume:
  - Very fine prediction by artery and time of day Artery
  - Similar results with density, time lags specifications
- Back

Road Technology: Robustness

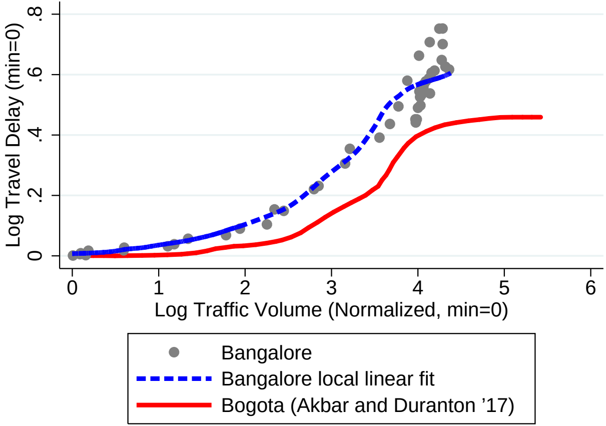
- Measuring speed. Robust to:
  - Measuring speed with GPS data
  - Controlling for trip characteristics
- Measuring traffic volume:
  - Very fine prediction by artery and time of day Artery
  - Similar results with density, time lags specifications
- Comparison to other settings:
  - Different from 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)
- Back

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

Back

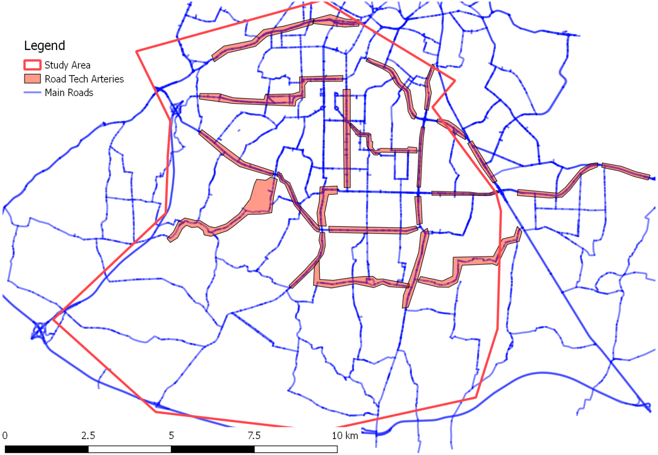
Road Technology Comparison



- Very similar to Akbar and Duranton (2017)
  - Concave part: time lags and/or survey data bias (Zhao et al 2015)

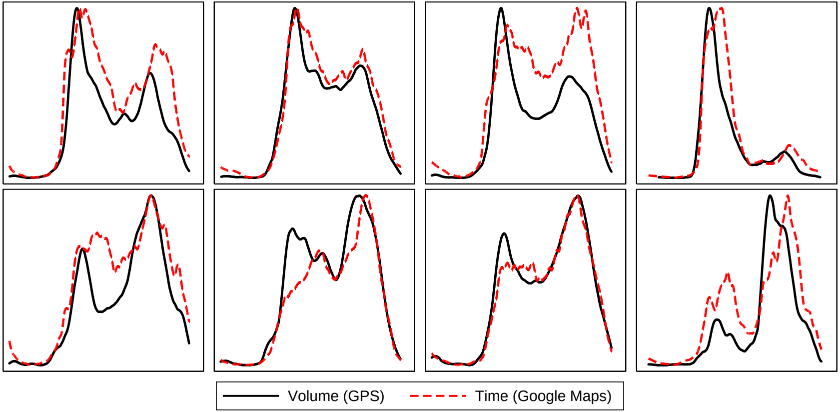
◂ Go Back

Road Technology at Artery Level



- 22 arteries with Google Maps travel time data (in both directions)

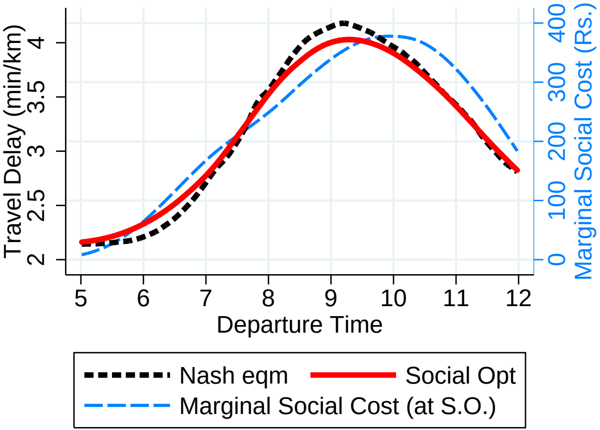
Road Technology at Artery Level



- Traffic volume (GPS) predicts travel time **profile** (Google Maps)
  - Adj $R^2 = 60\%$ with time-of-day FE, artery FE, artery-specific slopes

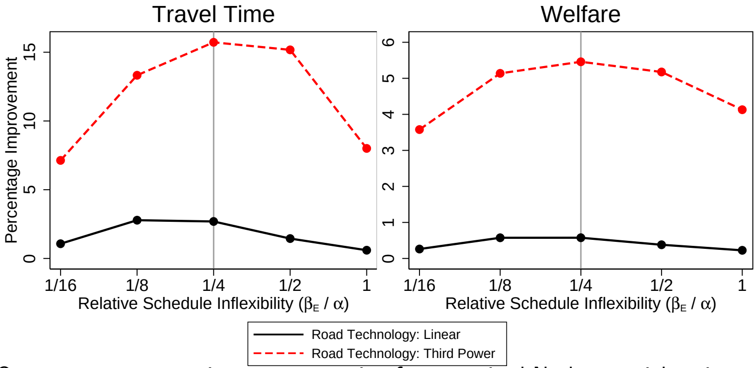
Sample Selection
Road Technology

Social Optimum with Marginal Social Cost



- MSC higher after peak-hour: pushing others towards the peak Back

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

Nash Eqm

Back

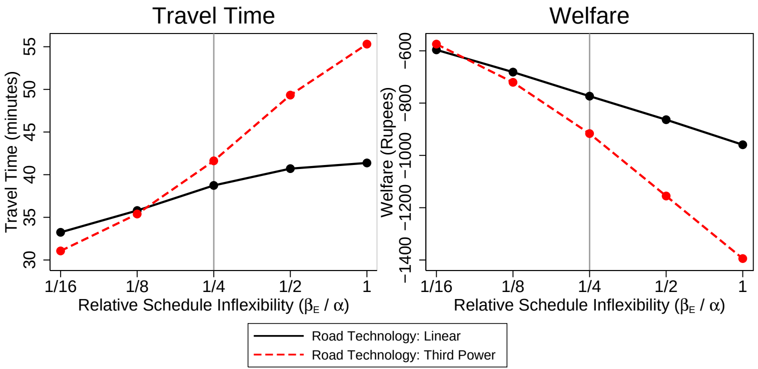
Inefficiency with Preferences Heterogeneity

Distribution	(1) $\mathrm{SD}(\alpha_i)/\bar{\alpha}_i$	(2) $\mathrm{Corr}(\alpha_i, \beta_i)$	(3) Nash Welfare	(4) % Inefficiency
Binomial	0.33	1	-774.8	0.71%
Log-normal	0.44	1	-772.2	0.85%
Log-normal	0.44	0	-743.4	0.60%

- Binomial $\left(\alpha_i^H, \beta_i^H\right) = \left(2\alpha_i^L, 2\beta_i^L\right)$ or continuous (log-normal) heterogeneity
- Moderate heterogeneity in (α_i, β_i) does not change conclusion

Back

Flexibility Compensates for Bad Road Technology



Outcome: unpriced Nash equilibrium

- High schedule flexibility (low β_E/α) diminishes the negative effect of convex road technology

Back

Social Optimum: Notable Travel Time Benefit...

	(1)	(2)
	Travel Time (min.)	
		Above Free-Flow
Nash equilibrium	38.7	16.7
Social Optimum	37.7	15.7
Improvement	1.04	1.04
Improvement (% of Nash)	2.7%	6.2%

... But Modest *Welfare* Gain

	(1) Travel Time (min.)	(2) Travel Time (min.) Above Free-Flow	(3) Welfare (Rupees)	(4) Welfare (Rupees) Above Free-Flow
Nash equilibrium	38.7	16.7	-773.4	-337.8
Social Optimum	37.7	15.7	-769.0	-333.3
Improvement	1.04	1.04	**4.46**	**4.46**
Improvement (% of Nash)	2.7%	6.2%	**0.6%**	**1.3%**

- Schedule costs comparable to benefits (externality + value of time)

... But Modest *Welfare* Gain

	(1)	(2)	(3)	(4)
	Travel Time (min.)		Welfare (Rupees)	
		Above Free-Flow		Above Free-Flow
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Inefficiency with Extensive Margin Decision

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

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

Value of trip (Rs.)	Trip Probability Nash	Social Opt.	Improvement (% of Nash)
800	0.06	0.06	0.0%
900	0.49	0.45	1.6%
1,000	0.94	0.73	6.2%
1,100	1.00	0.82	4.5%
1,200	1.00	0.89	2.7%
1,300	1.00	0.95	1.6%

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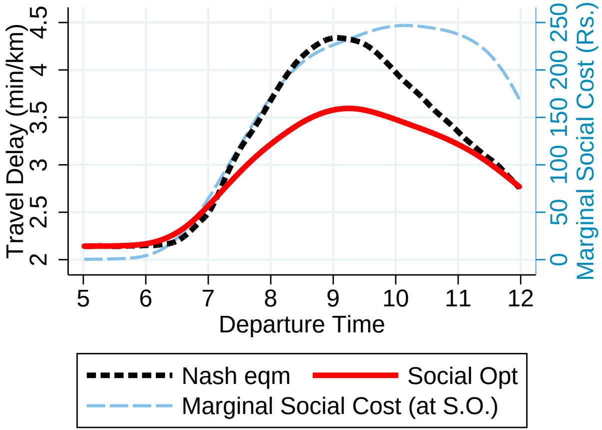
Inefficiency with Extensive Margin Decision

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



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