Measuring Commuting and Economic Activity inside Cities with Cell Phone Records

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Data on Economic Activity *within* Cities Valuable yet Scarce

- Detailed spatial data on firms, jobs, wages is important for policymakers and researchers.
- Useful for analyzing localized shocks within cities: floods, violence, industry-specific demand shocks, transportation policy, etc.
- However, such data is generally scarce.

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Full Sub-Saharan Africa Sample	27	100%
Have Economic Census ...	16	45%
... and Covers Informal Firms	11	25%
... and Wage Data	≤ 4	$< 9\%$

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This Paper: Use Commuting Flows from Cell Phone Data to *Infer* Wages

Two facts:

1. Economic activity in cities intertwined with commuting behavior
2. Rich data on urban mobility increasingly available

1. **Data: cell phone transactions** in Colombo, Sri Lanka, and Dhaka, Bangladesh
   - Construct and validate **commuting flows**
2. **Method** to recover labor productivity data from commuting patterns
   - Based on gravity equation
   - Unlike machine learning, no training data necessary
   - We show validation results
3. Showcase **application**: impact of *hartal* strikes in Dhaka

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Cell Phone Transaction Data (CDR) from Sri Lanka and Bangladesh

- Data from Dhaka and Colombo around 2013 Data Coverage
  - 8 million anonymized user IDs
  - for each call: user ID, timestamp, cell phone tower location
  - no data on: gender, education, occupation, etc.
- Construct commuting flows by observing the same SIM card on the same day (morning and afternoon)
  - 440 million days with commuting information
  - Results robust to using "common" day and night places
- CDR commuting flows correlate well with survey commuting flows in Dhaka

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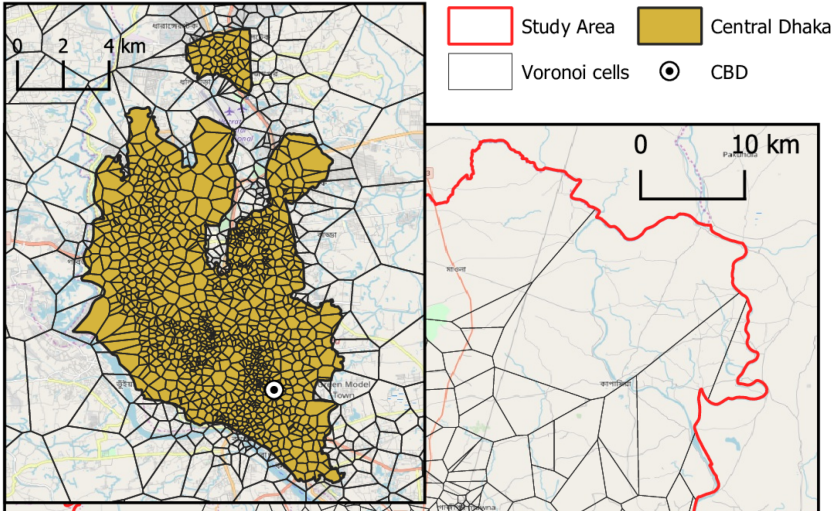
Geographic Unit: Cell Phone Tower Voronoi Cells – Dhaka, Bangladesh



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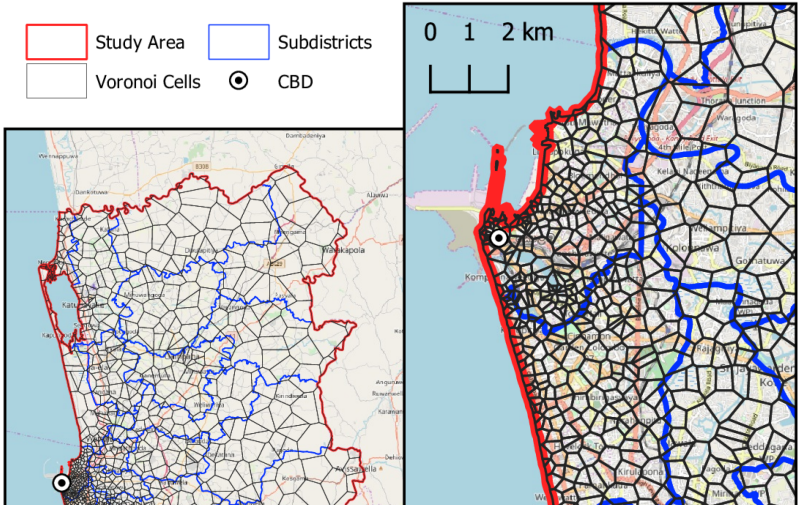
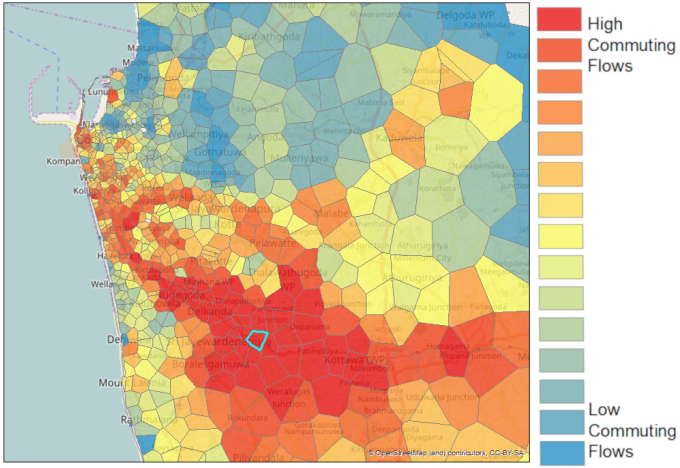
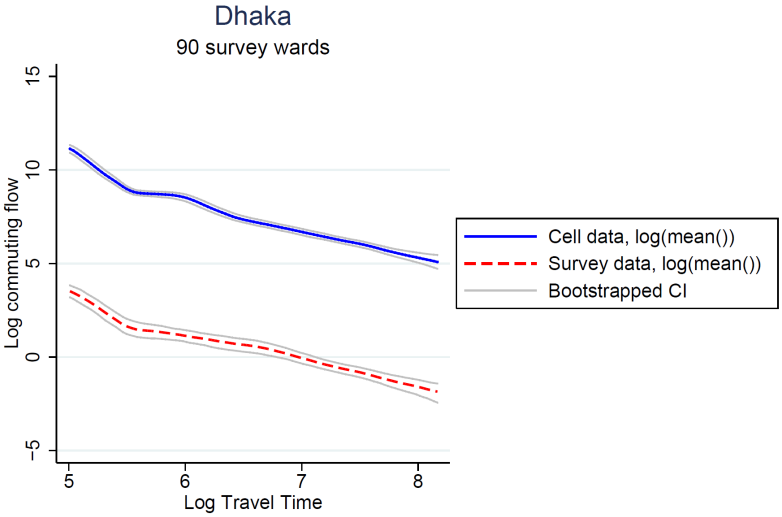


Example: Commuting Flows from a Single Origin Tower (Colombo)



Commuting Flows from CDR vs Survey Data (Dhaka)

Commuting flows between pairs of survey wards



The Logic of our Method

- Hypothesis: work destinations with high wages attract more workers, *ceteris paribus*.
- Gravity equation: regress commuting flows on travel time and origin and destination factors
  - Estimate **destination attractiveness**
  - Interpret as measure of wages
- Quantitatively motivated by simple version of urban economic model (Ahlfeldt et al 2015, Heblich et al 2018, Tsivanidis 2019, Severen 2019)
  - Procedure has nice theoretical properties

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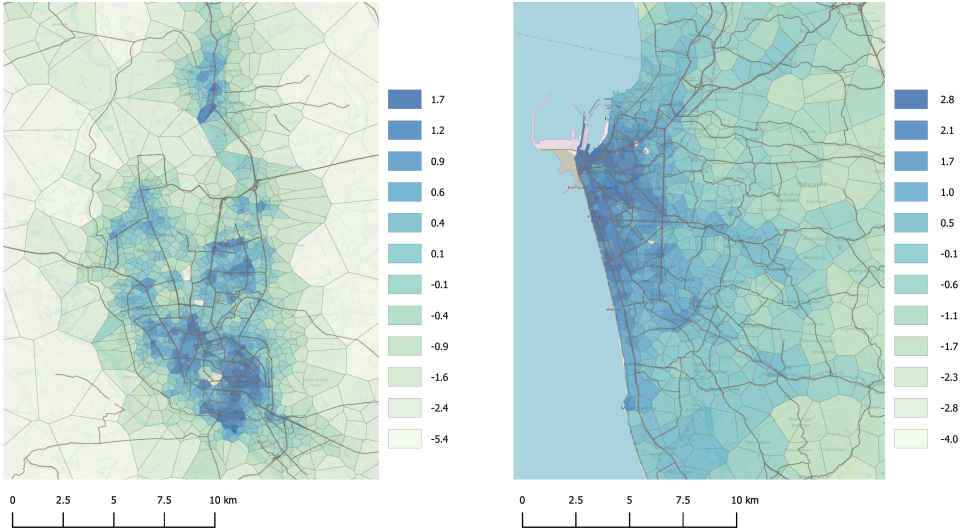
Estimated (smoothed) log Wages in Dhaka and Colombo

Figure 1: Estimated log Wages in Dhaka and Colombo



Validating Model-Predicted Income with Other Data Sources

- Model-predicted income is computed without "training" data
  - Only uses **commuting behavior** and **Google Maps travel times**
- Model: we know how income "moves" across the city
  - We compute income at *workplace* and at *residential* level
- Two validation exercises. Compare:
  1. Model *workplace* income and survey workplace income
  2. Model *residential* income and nighttime lights

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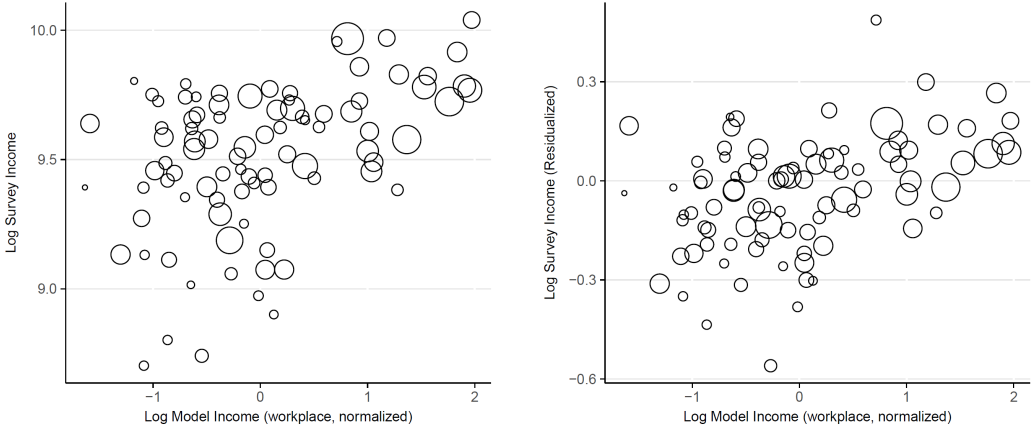
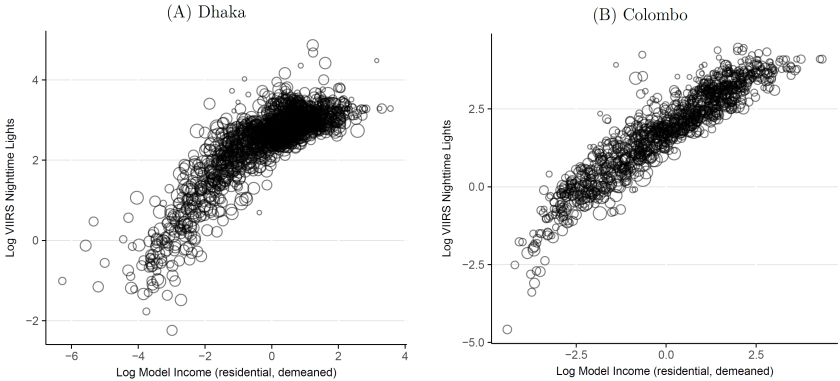
Validation at *Workplace*: Model Income and Survey Income

(A) Model and Survey Workplace Income



Validation at *Residential*: Model Income and VIIRS Nighttime Data

- Nighttime satellite lights proxy of country GDP growth (Henderson et al 2010)
- Within cities, intuitively nightlights capture *residential* income



Discussion: How to Judge Model Predictive Performance?

- Model-predicted income consistently statistically significantly predictive of income from other sources

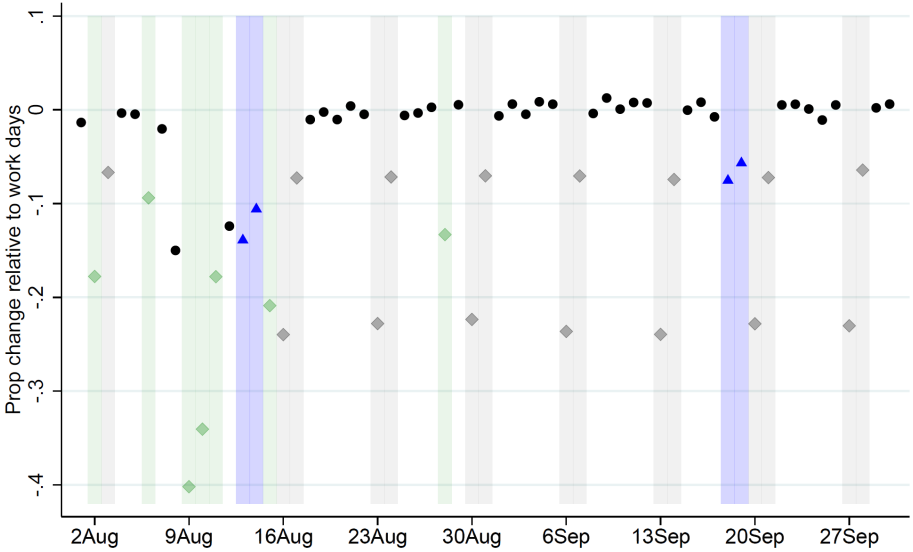
- However, predictive power for income from survey data is modest ($R^2 \approx 0.3$).
  1. Survey data itself not perfect
  2. Difficult prediction problem *within* cities
  3. In fact, machine learning approaches predict income with similar accuracy when looking at cities only (Blumenstock et al 2015, Jean et al 2016)

The Impact of Hartals in Dhaka

- Hartals are strikes in Bangladesh that involve partial shutdowns of urban transportation and businesses.
- 31 hartal days in 4 months in late 2013 in Dhaka (we use data from Ahsan and Iqbal, 2015)
- Objective: use rich commuting data and model predictions to estimate income losses due to hartal
- Accounting exercise:
  1. Measure income changes due to commuting changes.
  2. Assume that wages stay constant.

Hartal

Average Model-predicted Income is Lower on Hartal Days



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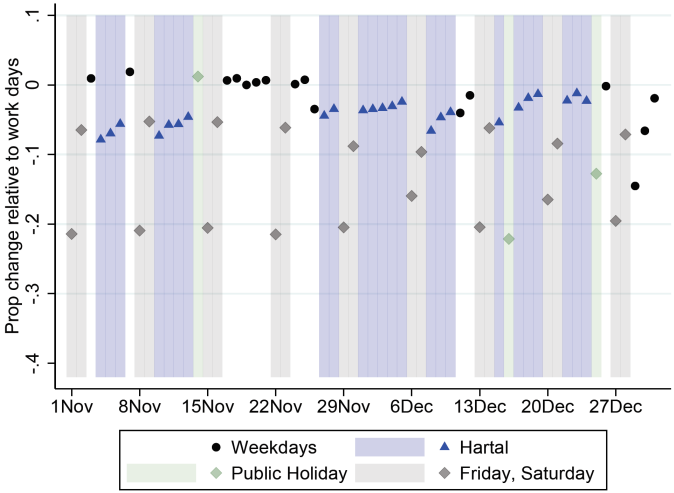

Commuters in Dhaka Travel and Earn Less on Hartal Days

- Commuters in Dhaka earn on average 4.4 to 4.8% less on hartal days compared to workdays
  - Effects much smaller compared to Fridays (20 to 45% lower predicted income)
- Effects driven primarily by the extensive margin, namely fewer trips
- Commuters with longer trips reduce trips relatively more
- Commuters working in high-income destinations reduce trips relatively more, controlling for trip duration

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Conclusion: Using Big Data to Measure Revealed Preferences

- Used cell phone data to construct (a) commuting, and (b) detailed urban economic activity measures
- Income from this method predicts survey income and nighttime lights
- Potential applications: analyzing urban shocks localized in space and/or time
- Big data for revealed preferences: route choice (safety: Borker 2016), value of public services, payments (informal economic activity)

Thank you!

Cell Phone Data Coverage

Table C.1: Cell Phone Data Coverage at User-Day Level

		Dhaka, Bangladesh	**Colombo, Sri Lanka**
(1)	Users in sample	$5.3 \cdot 10^6$	$3.0 \cdot 10^6$
(2)	Days in sample	122	395
(3)	All user-days possible = (1)×(2)	$6.5 \cdot 10^8$	$1.2 \cdot 10^9$
(4)	User-days with data	$2.9 \cdot 10^8$	
(5)	User-days with data (5-10am)	$1.5 \cdot 10^8$	
(6)	User-days with data (10am-3pm)	$2.4 \cdot 10^8$	
(7)	User-days with data (5-10am and 10am-3pm)	$1.0 \cdot 10^8$	$3.4 \cdot 10^8$
(8)	Coverage rate =(7)/(3)	16.1%	28.8%

Back