Clearing the Air on the Benefits and Costs of Road Infrastructure

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Motivation

- Expanding transportation infrastructure regarded as catalyst for economic development (Redding and Turner 2015, Foster et al. 2023)
- But may also impose significant costs on local residents via air pollution from traffic
  (Currie and Walker 2011, Heissel et al 2022, Knittel et al 2016)
- Costs especially pronounced in rapidly urbanizing developing country cities:
  - High traffic congestion
  - Weak environmental regulation
  - Severe pollution impacts: 5.3 year life expectancy cost in Lahore (Greenstone & Fan 2019)

Research questions

- What is the role of traffic in shaping pollution levels?
- When accounting for pollution: how do gains from urban road infrastructure compare with losses?
  - On average
  - By location

This paper's setting: Lahore, Pakistan

Record Air Pollution Hospitalizes Hundreds in Pakistani City

The authorities in Lahore, home to 13 million people and the country's second-biggest city, have told half the work force to stay home.

New York Times, 7 November 2024

Nov 2019: Annual Sports Day of FCC College

PM2.5 $> 1000\ \mu g/m^3$

This paper

- Present empirical evidence showing that traffic is a non-negligible contributor to pollution concentrations in this setting
- Develop quantitative urban equilibrium model integrating atmospheric pollution dispersion
- Calibrate using novel data on emissions, pollution, commuting, goods trade in Lahore
- Estimate distribution of economic and pollution-related impacts from road improvements

Preview of (preliminary) results

- Pollution significantly alters aggregate and distributional impacts of road investments
- Lahore ring road, major orbital highway constructed 2012-2024:
  - Aggregate welfare gains substantially lower when accounting for local air pollution
  - Air pollution changes conclusion about whether ring road improves welfare for 27% locations
- Welfare gains from shutting down some road edges
  - 25% roads have *negative* aggregate welfare effects when incorporating local pollution impacts

Outline

Motivating evidence on traffic and pollution in Lahore

Model

Implementation

Counterfactuals

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Combine several georeferenced data sources

Outcomes:

- PM2.5 concentrations, from 113k hourly readings from 13 ground-level air quality sensors in and around Lahore

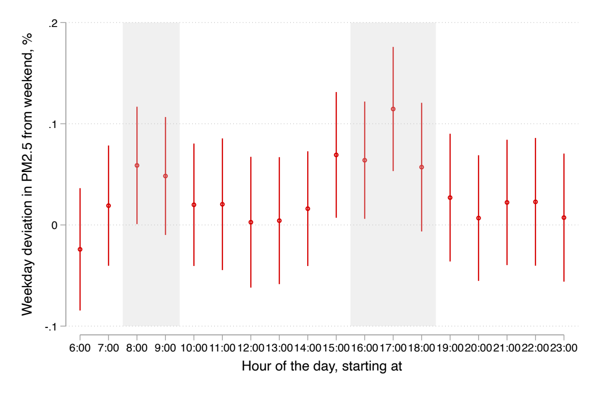
Regressors:

- Meterological data (temperature, humidity, wind speed, precipitation, cloud cover)
- Traffic: GPS tracker signals on commercial trucks from an original equipment manufacturer (Balboni et al., 2024)
    - 18m edge-day-vehicle observations; 4,900 trucks in 2018.

Pollution peaks during rush hour, consistent with key role of traffic

Graph shows **weekday deviations** ($\rightarrow$ rush hour) of PM2.5 concentrations from (de-meaned) averages

Morning rush hr: +5%, uncond. avg.: 100µg/m^3;
Evening rush hr: +10%, uncond. avg.: 65µg/m^3



Notes: The graph shows the average weekday (Monday to Thursday) deviations in $PM_{2.5}$ concentrations, in percent, from the unconditional averages, by hour of the day. Shaded regions correspond to the morning and evening rush hours. The underlying regression excludes Fridays (because or less regular work hours due to Friday prayers), and includes sensor, day, and hour-of-the-day fixed effects as well as controls for third-order polynomials in temperature, humidity, wind speed, precipitation, and cloud cover. The regression weighs observations by the inverse of the number of observations available for each sensor, to correct skewness in data availability.

Meteorological conditions affect influence of emissions on pollution

Wind speed, temperature, humidity, cloud cover, precipitation etc all affect PM2.5 concentrations.

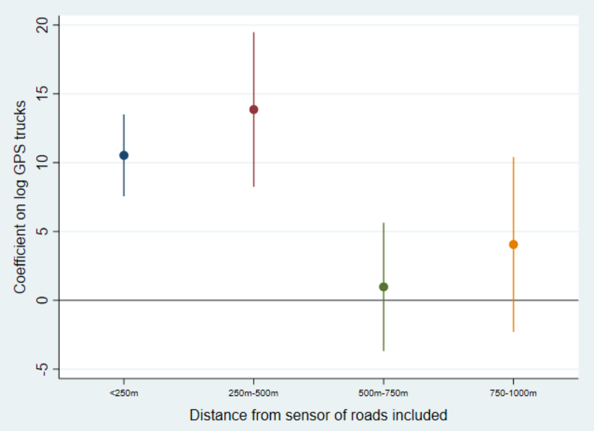
It's complicated. We know from physics/chemistry that concentrations are not linear in these determinants.

	Dependent variable: PM2.5 concentration (ug/m3)				
	(1)	(2)	(3)	(4)	(5)
Weekend dummy	-17.93***	-22.15***	-19.90***	-24.59***	-22.65***
	(2.21)	(2.07)	(2.98)	(2.88)	(2.74)
Ramadan dummy	-21.38***	-20.07***	-49.55***	-13.46	-47.25***
	(5.57)	(5.70)	(9.52)	(11.2)	(9.71)
Log GPS trucks			7.479***	7.916***	9.438***
			(2.01)	(1.94)	(1.90)
Wind speed (std)		-12.80		-13.68***	-37.15**
		(10.9)		(1.57)	(11.9)
Temperature (std)		-45.99***		-57.92***	-50.57***
		(5.51)		(3.90)	(5.99)
Humidity (std)		-38.70***		16.90***	-31.66***
		(4.31)		(2.00)	(6.77)
Cloud cover (std)		34.91*		7.291***	-2.016
		(17.0)		(1.52)	(20.7)
Precipitation (std)		-0.311		-2.194*	-1.291
		(3.39)		(1.11)	(3.98)
Inv Ventilation coeff (std)		16.50***		0.314	24.27***
		(4.78)		(1.78)	(6.11)
Sensor FE	X	X	X	X	X
Hour of the day FE	X	X	X	X	X
Week FE	X	X	X	X	X
Additional controls		X			X
R^2	0.595	0.647	0.599	0.627	0.658
Observations	112329	103693	34380	31727	31727

Impacts of traffic on local pollution are highly localized

Coefficients on traffic in range bins:

- < 250m,
- 250-500m,
- 500-750m,
- 750-1000m



Notes: Each point represents the estimated coefficient on Log GPS trucks from separate regression of $PM_{2.5}$ concentrations on Log GPS trucks, weekend and Ramadan dummies, and meteorological controls (wind speed, temperature, humidity, cloud cover, precipitation, and the inverse of the ventilation coefficient), where the distance within which roads are included in the traffic variable changes across regressions (eg. 250-500m only includes GPS signals from roads at a distance between 250m and 500m from each sensor).

Outline

Integrated spatial-environmental framework

- Quantitative spatial equilibrium model of Lahore integrating:
  - Commuting and trade frameworks (Allen & Arkolakis 2022)
  - Emissions and dispersion of local air pollutants (ADMS-Urban):
    - to simulate dispersion & mixing of pollutant particles under counterfactual scenarios

- Key features:
  - Workers commute from residence to work locations, firms produce and trade goods varieties
  - Emissions generated by production, trade, commuting; transported by atmospheric processes
  - Pollution at residence (workplace) $\downarrow$ utility (productivity), influences workplace and commute
  - Externalities: productive agglomeration, traffic congestion, pollution transport

Model setup

- **Geography**: graph G with vertices ("locations") I connected by edges ("roads") E
  - Fixed residential population of L_i^0
- **Workers**: live in i, choose work location j and route from i to j from set $\mathfrak{R}_{ji}$
  - m_j pollution concentrations, w_j wages
  - Pollution at j reduces productivity (e.g. Adhvaryu et al 2022, Hoffman & Rud 2024) $\rightarrow$ supply $m_j^{-\sigma_w}$ effective labor units
  - Perfectly competitive labor market in each location $\rightarrow$ labor income $m_j^{-\sigma_w} w_j$
  - Purchase consumption goods in work location with bundle of varieties and price index:

$$c_j = \left[\int_0^1 c_j(s)^{\frac{\varepsilon-1}{\varepsilon}} ds\right]^{\frac{\varepsilon}{\varepsilon-1}}, \qquad p_j = \left[\int_0^1 p_j(s)^{1-\varepsilon} ds\right]^{\frac{1}{1-\varepsilon}}$$

Household utility

Utility of a worker ω living in i commuting to j via route $r = (r_1, r_2, \ldots, r_K(r))$:

$$V_{ji,r}(\omega) = \underbrace{m_i^{-\sigma_h}}_{\text{Disutility from home pollution}} \times \underbrace{\frac{m_j^{-\sigma_w} \times w_j}{p_j}}_{\text{Real consumption}} \times \underbrace{\left[\prod_{l=1}^{K(l)} t_{r_{l-1},r_l}\right]^{-1}}_{\text{Commuting cost}} \times \underbrace{\eta_{ji,r}(\omega)}_{\text{Idiosyncratic shock}}$$

where:

- σ_h: elasticity of utility wrt pollution concentration at residential location
- t_e: commuting cost on edge e
- $\eta_{ji,r}$: idiosyncratic route-specific shock (Fréchet with shape θ)

$\Rightarrow$ Probability for household i to work in j:

$$\omega_{ji} = \frac{m_j^{-\theta\sigma_w} w_j^{\theta} p_j^{-\theta} \tau_{ji}^{-\theta}}{\sum_{j'} m_{j'}^{-\theta\sigma_w} w_{j'}^{\theta} p_{j'}^{-\theta} \tau_{j'i}^{-\theta}} \qquad \text{with} \qquad \tau_{ji} \equiv \left[\sum_{r \in \mathfrak{R}_{ji}} \left(\prod_{l=1}^{K(r)} t_{r_{l-1},r_l}^{-\theta}\right)\right]^{-\frac{1}{\theta}}$$

Firms

- Perfectly competitive firms at i produce goods varieties using labor: $y_i(s) = l_i(s)$
- Cost of offering one unit of variety s from i to j via route r:

$$p_{ji,r}(s) = w_i \frac{\prod_{k=1}^{K(r)} t_{r_{k-1},r_k}}{\varepsilon_{ji}(r,s)} \quad \text{where} \quad P(\varepsilon_{ij}(r,s) < x) = \exp\left(-A_i^{\theta} x^{-\theta}\right)$$

$\Rightarrow$ probability for firms in j to source from i:

$$\pi_{ji} = \frac{\left(w_i/A_i\right)^{-\theta} \tau_{ji}^{-\theta}}{\sum_{i'} \left(w_{i'}/A_{i'}\right)^{-\theta} \tau_{ji'}^{-\theta}}.$$

- Labor supply in each location:

$$L_j = m_j^{-\sigma_w} \sum_i \omega_{ji} L_i^0 \tag{1}$$

where ω_{ji} is share of workers in i commuting to j

Analytic expressions for traffic (Allen-Arkolakis '22)

- Value of goods flows from location l to location k connected via an edge e:

$$\Xi_e^y = t_{kl}^{-\theta} \times p_l^{-\theta} \times \Pi_k^{-\theta} \tag{2}$$

- Mass of commuter flows on an edge e:

$$\Xi_e^l = t_{kl}^{-\theta} \times \Psi_k^{-\theta} \times \Theta_l^{-\theta} \tag{3}$$

where

$$\Pi_i \equiv \underbrace{\left(\sum_j \tau_{ji}^{-\theta} p_j^{\theta} Y_j\right)^{-\frac{1}{\theta}}}_{\text{Inverse producer market access}},\ \Psi_k \equiv \underbrace{\left(\sum_i m_i^{-\theta\sigma_w} \tau_{ik}^{-\theta} w_i^{\theta} p_i^{-\theta}\right)^{-\frac{1}{\theta}}}_{\text{Inverse labor market access of households}},\ \Theta_l \equiv \underbrace{\left(\sum_j \tau_{lj}^{-\theta} \Psi_j^{\theta} L_j^0\right)^{-\frac{1}{\theta}}}_{\text{Inverse access of firms to workers}}$$

Externalities

1. Positive agglomeration externalities: $A_i = \bar{A}_i L_i^{\alpha}$ (4)

2. Congestion externalities from traffic: $t_e = \bar{t}_e \left(\nu \Xi_e^y + \Xi_e^l\right)^{\lambda}$ (5)

   - ν weights average goods vs commuter traffic using passenger-car equivalents of vehicles (Chandra & Sikdar 2000; Sharma & Biswas 2021)

3. Air pollution externalities:

$$m_j = \underbrace{\sum_{i \in I} \gamma_{ji} \mu_y Y_i}_{\text{Pollution from industry}} + \underbrace{\sum_{e \in E} \gamma_{je} \mu_{\Xi_y} \Xi_e^y}_{\text{Pollution from goods traffic}} + \underbrace{\sum_{e \in E} \gamma_{je} \mu_{\Xi_l} \Xi_e^l}_{\text{Pollution from commuter traffic}} \quad (6)$$

- $\Gamma = (\gamma_{ji})_{j,i}$ governs steady state concentration increase γ_{ji} in j from emissions in i
- μ_y, μ_{Ξ_y}, μ_{Ξ_l} emissions per unit of production output, goods traffic, commuter traffic

Equilibrium

For a given graph G with productivity $\{\bar{A}_i\}_{i\in I}$, infrastructure $\{\bar{t}_e\}_{e\in E}$ and residential populations $\{L_i^0\}_{i\in I}$, equilibrium is distribution of labor and production $\{L_i, Y_i\}_{i\in I}$ such that:

1. Labor supply determined by commuting decisions and pollution according to (2)
2. Households maximize utility
3. Firms choose labor inputs and distribution routes to maximize profits
4. Productivities, transportation costs, concentration levels satisfy (4), (5), (6) respectively
5. Traffic levels consistent with commuting and transportation route choices
6. Goods and labor markets clear

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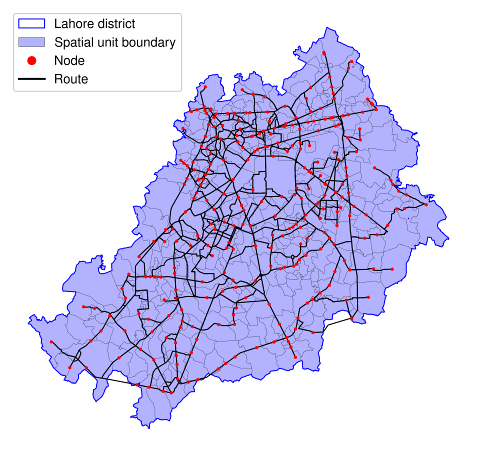
Empirical Implementation of the Model

Locations = 361 'mauzas' (Urban Unit), network of major roads (OpenStreetMap)

- Aggregate mauzas with no major roads to closest mauza ⇒ 287 locations
- Extract edges connecting adjacent location centroids from pairwise least-cost paths



Currently working on finer economic geography (not today ▸ ok, fine)

Data Inputs

- **Residential population L_i^0**
  - Population density at 30m from Meta (2021) using satellite imagery and census data
- **Commuting traffic: mobile phone signals from Quadrant (2024)**
  - GPS observations: device ID, timestamp, geocoordinates
  - 198mn signals from 388,000 devices across Lahore during 2019
  - Yields commuting matrix ω_{ij} (Kreindler-Miyauchi '23). Project on edges to get Ξ^l.
- **Goods traffic: truck location signals**
  - GPS tracker signals from commercial trucks from original equipment manufacturer
  - 18mn edge-day-vehicle observations from 4,900 commercial trucks in 2018
  - Project on edges (and scale; Garg et al. '23) to get Ξ^y
- **Goods traffic: traffic surveys**
  - Traffic volumes, vehicle types from 6 traffic surveys at 671 stations from 2010-2020

Local pollutant concentrations

Atmospheric dispersion model of pollution

Multi-Model Air Quality System (Hood et al 2018) calibrated to Punjab province (with assistance from CERC

- Captures pollution from local sources and long-range chemical transport/mixing
- Concentration of particulate matter ($PM_{2.5,10}$), NO_x over space and time
- Model inputs:
  - Hourly historical meteorological conditions (ECWMF ERA5)
  - Background chemical concentrations (CAMS reanalysis data)
  - Traffic emissions from traffic volumes (traffic surveys, truck GPS, population density) and exhaust and non-exhaust pollutant emissions factors (COPERT) by vehicle type
  - Gridded inventory of spatially aggregated non-traffic emissions in 23 sectors (EDGAR)

Validated using air quality data from pollution monitors (ground-level sensor data)

Counterfactual to change transportation costs $\bar{t}$: Goods Market

Exact-hat approach (Dekle et al., 2008)

Rewrite all equilibrium equations in changes $\hat{X} = X'/X$.

$$Y_i^{1+\theta} \bar{A}_i^{-\theta} L_i^{-\theta(1+\alpha)} = Y_i p_i^{\theta} + \sum_j t_{ji}^{-\theta} Y_j^{1+\theta} \bar{A}_j^{-\theta} L_j^{-\theta(1+\alpha)}$$

$$\downarrow$$

$$\hat{Y}_i^{1+\theta} \hat{L}_i^{-\theta(1+\alpha)} = \frac{Y_i}{Y_i + \sum_k \Xi_{ki}^{y}} \hat{Y}_i \hat{p}_i^{\theta} + \sum_j \frac{\Xi_{ji}^{y}}{Y_i + \sum_k \Xi_{ki}^{y}} \hat{t}_{ji}^{-\theta} \hat{Y}_j^{1+\theta} \hat{L}_j^{-\theta(1+\alpha)}$$

- Ξ_{ki}^{y} GPS truck data, projected on edges, scaled by average value of truck shipment (Garg et al., 2023)
- Y_i from Pakistani value added tax data (Balboni et al., 2024)

Counterfactual to change transportation costs $\bar{t}$: Labor Market

$$L_j^{1+\theta} Y_j^{-\theta} p_j^{\theta} m_j^{(1+\theta)\sigma_w} = \sum_i t_{ji}^{-\theta} L_i^{1+\theta} Y_i^{-\theta} p_i^{\theta} m_i^{(1+\theta)\sigma_w} + m_j^{-\theta\sigma_h} \bar{W}_j^{-\theta} L_j^0$$

$$\downarrow$$

$$\hat{L}_i^{1+\theta} \hat{Y}_i^{-\theta} \hat{p}_i^{\theta} \hat{m}_i^{(1+\theta)\sigma_w} = \frac{L_i^0}{\sum_k \Xi_{ik}^l + L_i^0} \hat{m}_i^{-\theta\sigma_h} \widehat{\bar{W}}_i^{-\theta} \hat{L}_i^0 + \sum_j \frac{\Xi_{ij}^l}{\sum_k \Xi_{ik}^l + L_i^0} \hat{t}_{ij}^{-\theta} \hat{L}_j^{1+\theta} \hat{Y}_j^{-\theta} \hat{p}_j^{\theta} \hat{m}_j^{(1+\theta)\sigma_w}$$

- Ξ_{ki}^l Cellphone data projected on edges, scaled to match average AADT commuter traffic in surveys (on survey edges)
- L_i^0 from Meta gridded population data

Counterfactual to change transportation costs $\bar{t}$: Pollution Concentrations

$$m_j = \sum_{i \in I} \gamma_{ji} \mu_y Y_i + \sum_{e \in E} \gamma_{je} \mu_{\Xi_y} \Xi^y_e + \sum_{e \in E} \gamma_{je} \mu_{\Xi_l} \Xi^l_e$$

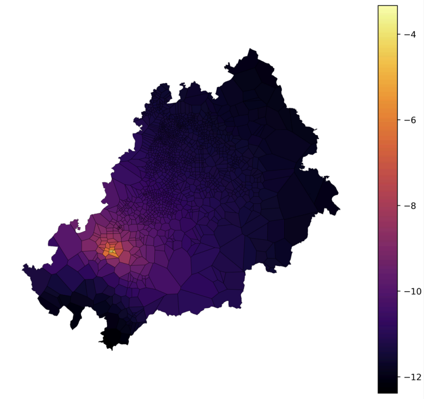
$$\downarrow$$

$$\hat{m}_i = \sum_j \hat{Y}_j \mathbf{M}^y_{ij} + \sum_{j,k} \hat{\Xi}^y_{jk} \mathbf{M}^{\Xi^y}_{i,jk} + \sum_{j,k} \hat{\Xi}^\ell_{jk} \mathbf{M}^{\Xi^\ell}_{i,jk}$$

- $\mathbf{M}^y_{ij}, \mathbf{M}^{\Xi_y}_{ij}, \mathbf{M}^{\Xi_\ell}_{ij}$: concentration share in i from industrial, goods traffic, commuter traffic in j

1. Estimate pollution transport matrix γ_{ij} using ADMS model (2018, avg'ed)
2. Estimate μ_y using gridded top-down sectoral emissions inventory (EDGAR)
3. Generate $\mathbf{M}^y_{ij}, \mathbf{M}^{\Xi_y}_{ij}, \mathbf{M}^{\Xi_\ell}_{ij}$ using γ_{ij}, μ_y and output in each location

Example of a row γ_{ij}



Notes: This figure shows an example of γ_{ij} for a given row i. These can be interpreted as the proportion of concentrations in mauza i which are attributable to mauza j. These are calculated using the source apportionment option of the ADMS model with mauzas modelled as areas with homogenous emissions, receptors placed in a 500m$\times$500m grid and using 2018 meteorological data. γ_{ij} are calculated as the PM2.5 concentration from mauza j as a share of concentration from all sources, averaged across all receptors in i.

Counterfactual to change transportation costs $\bar{t}$: Congestion

ν: weight on truck traffic in pollution expression

$$t_{kl}^{-\theta} = \bar{t}_{kl}^{-\frac{\theta}{1+\lambda\theta}} \left(\nu p_l^{-\theta} Y_k^{1+\theta} \bar{A}_k^{-\theta} L_k^{-\theta(1+\alpha)} + \bar{W}_k^{\theta} m_k^{\theta\sigma_h} L_l m_l^{(1+\theta)\sigma_w} w_l^{-\theta} p_l^{\theta} \right)^{-\frac{\theta\lambda}{1+\lambda\theta}}$$

$$\downarrow$$

$$\hat{t}_{kl}^{-\theta} = \widehat{\bar{t}}_{kl}^{-\frac{\theta}{1+\lambda\theta}} \left(\frac{\nu \Xi_{kl}^{y}}{\nu \Xi_{kl}^{y} + \Xi_{kl}^{l}} \hat{p}_l^{-\theta} \hat{Y}_k^{1+\theta} \hat{L}_k^{-\theta(1+\alpha)} + \left(\frac{\Xi_{kl}^{l}}{\nu \Xi_{kl}^{y} + \Xi_{kl}^{l}} \right) \widehat{\bar{W}}_k^{\theta} \hat{L}_l^{1+\theta} \hat{Y}_l^{-\theta} \hat{p}_l^{\theta} \hat{m}_k^{\theta\sigma_h} \hat{m}_l^{(1+\theta)\sigma_w} \right)^{\cdots}$$

- Calibrate $\nu = 5.01$ to match ratio of truck vs commuter traffic PCE on traffic survey edges

Calibrated elasticities

Parameter (with symbol)	Value	Method / source
Route elasticity (θ)	6.83	Allen & Arkolakis 2022
Traffic congestion elasticity (λ)	0.092	Allen & Arkolakis 2022
Agglomeration parameter (α)	-0.12	Allen & Arkolakis 2022
Relative congestion effect (ν)	5.01	TRB 2010, JICA 2010, Farooq & Akram 2018
Utility elasticity w.r.t. pollution (σ_h)	0.36	Greenstone et al 2025, Ebenstein et al 2017
Earnings elasticity w.r.t. pollution (σ_w)	0.09	Adhvaryu et al 2022

Outline

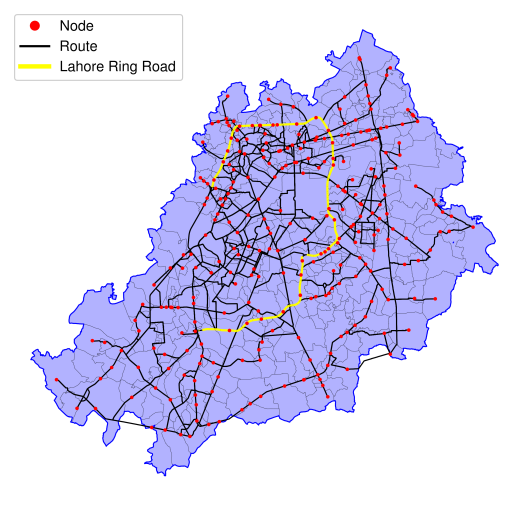
Counterfactual simulations

1. Does pollution change welfare assessment of road projects?
   - Evaluate opening of Lahore ring road from 2012-2024
2. Are there roads that have a net *negative* impact on welfare?
   - Estimate welfare effects of removing each road segment across city

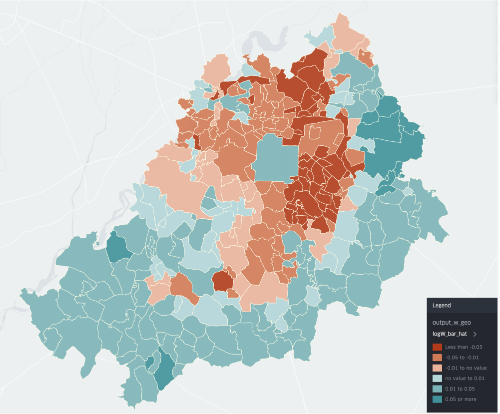
DISCLAIMER: Results are preliminary, numbers may change

Lahore ring road

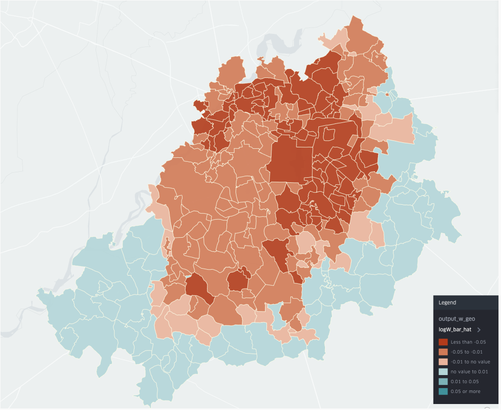
- Major orbital highway surrounding central city, opened in phases from 2012-2024
- Carries 400,000-500,000 vehicles daily
- Estimate aggregate and distributional implications of removing the Northern and Southern loops of the ring road (i) with and (ii) without accounting for air pollution impacts
- Counterfactual triples the cost of using any part of the ring road ($\hat{\hat{t}} = 3$)



Pollution alters aggregate and distributional impacts of ring road



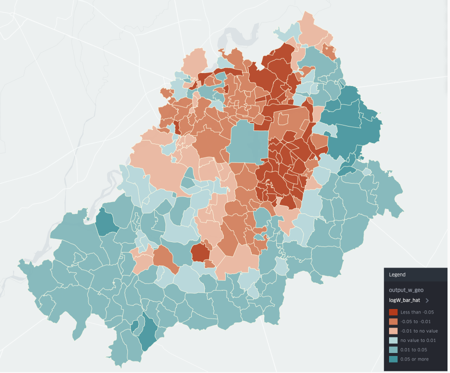
(a) Overall changes: $\Delta \log W^{\text{avg}} = -1.2\%$



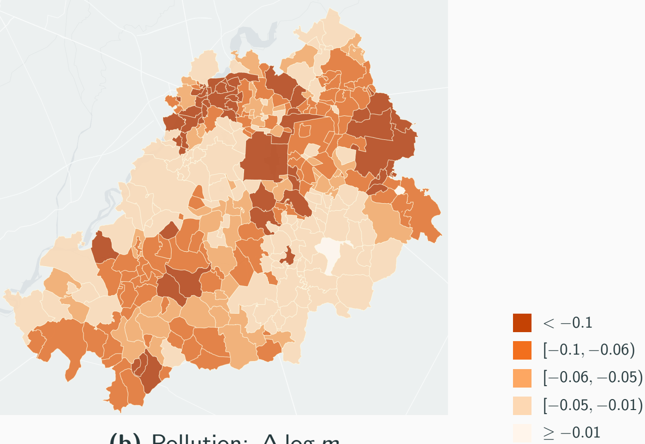
(b) Excluding pollution: $\Delta \log W^{\text{avg}} = -4.3\%$ $\sigma_h = \sigma_w = 0$

< -0.05 $[-0.05, -0.01)$ $[-0.01, 0)$ $[0, 0.01)$ $[0.01, 0.05)$

Some places are made better off despite losing market access



(a) Welfare: $\Delta \log W$



(b) Pollution: $\Delta \log m$

Places with net welfare gains despite loss in market access are those with large reduction in pollution concentrations

▸ $\Delta \log Y$

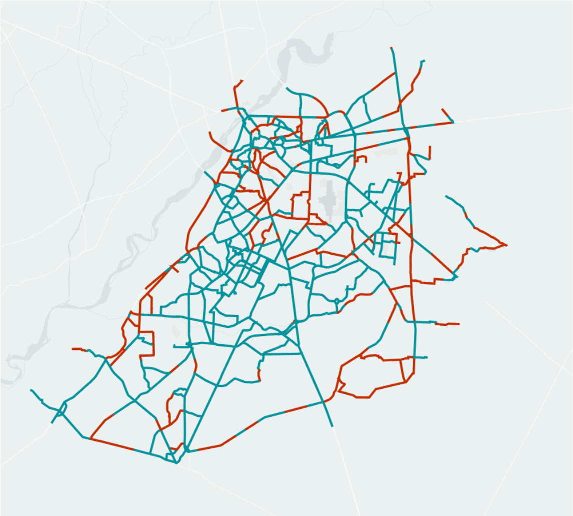
25% roads have negative aggregate welfare effects incorporating pollution

Loop over all roads:

For each road calculate population-weighted aggregate welfare if the road is switched off.

Roads where welfare goes up when road is shut down are colored in red.

▸ Euro-2 fuel standards



Notes: The figure shows the location of roads, colored in red, where aggregate (i.e. population-weighted) welfare $\bar{W}_i$ would increase when the road is shut down (simulated as a 100× increase in trade costs). All other roads are colored in green.

Conclusions

- Air pollution literature: "air pollution has large impacts on health, productivity, etc"
- Trade/spatial literature: "gains from market integration are small in standard static QSM/QTM"

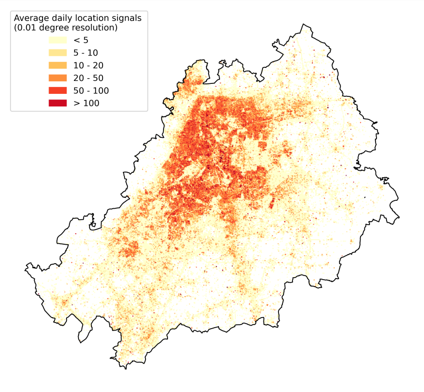
Integrated framework to compare both channels.

Take-aways:

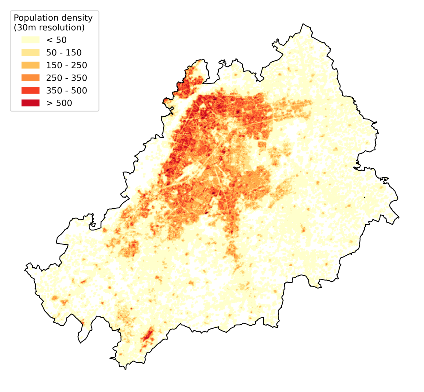
- Traffic is a non-negligible source of air pollution (in the context we study)
- Accounting for impacts from pollution can substantially affect welfare evaluation of transportation infrastructure
    - Aggregate & distributional impacts

BACKUP SLIDES

Mobile location data and population density



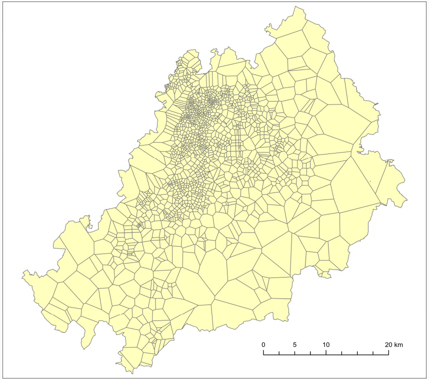
(a) Cellphone GPS signals



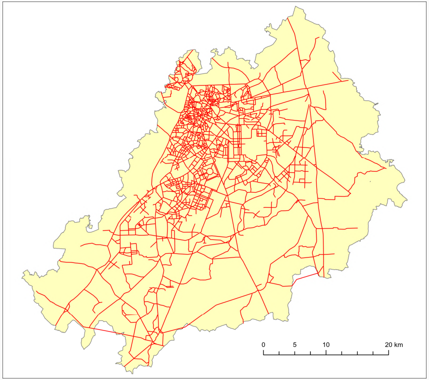
(b) Population density

▸ Back

More granular geography based on Voronoi cells



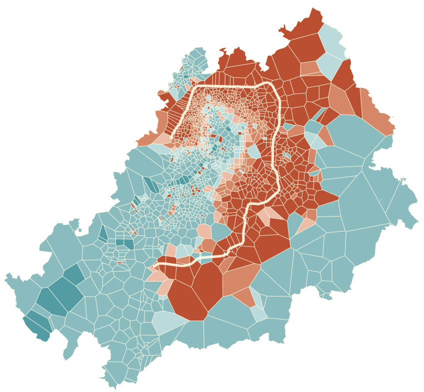
(a) Locations



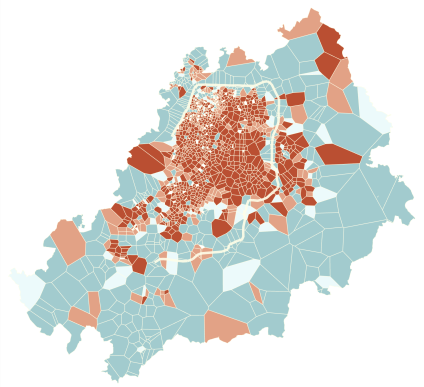
(b) Road network

Back

Shutting down Ring Road in detailed geography



(a) Net welfare changes (red = drop)



(b) Change in traffic-related pollution (red = worsening)

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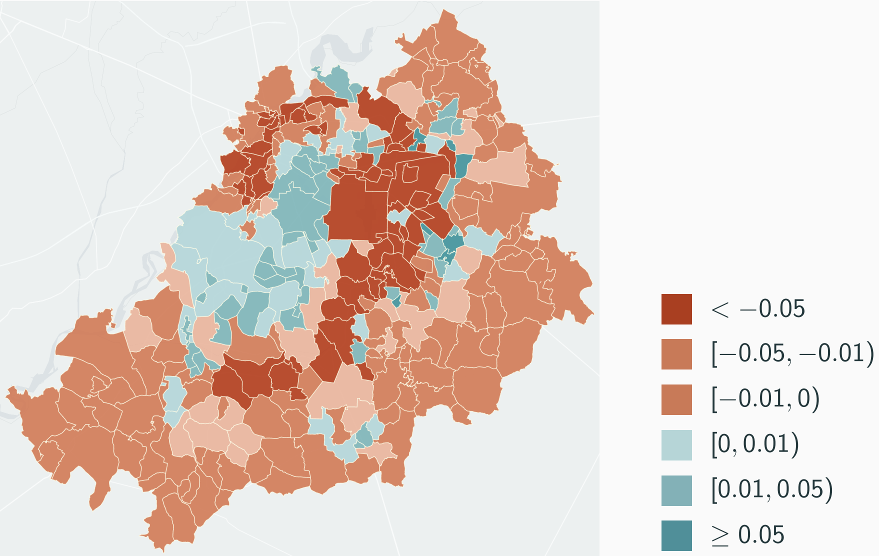
$\Delta \log Y$ from shutting down the Ring Road



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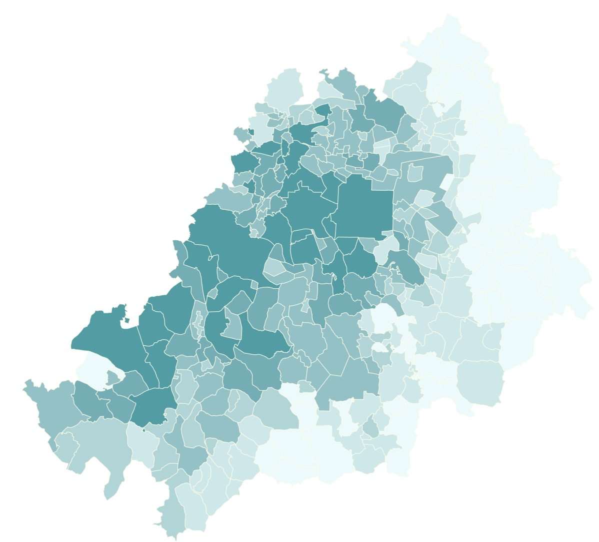
$\Delta \log W$ from moving to cleaner Euro-2 fuel standards: $\Delta \log W^{\text{agg}} = 8\%$



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