Accessibility in 1200 Cities and 400,000 Neighborhoods Worldwide[1]

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May 2025

[1]Disclosure: Funding for this project was provided by the World Bank, the International Growth Center, the Zell-Lurie Center at Wharton, and the Center for Innovative Data in Economic Research at UBC. The authors declare that they have no relevant financial relationships or conflicts of interest.

This Paper

- A methodology to measure accessibility to 100 venue types in 1200 cities and 400,000 neighborhoods worldwide.
- Decompose accessibility into two main components:
  1. Travel speed (from Google Maps)
  2. Distance to venues (from Google Places)
- Document a trade-off between speed and distance to venues across cities.

What we Find

- Accessibility trade-off: closer distance to venues correlates with slower travel speed.
  - Speed and distance have a 0.76 correlation between cities in the United States.
  - Despite speed-distance trade-off, denser cities still have better accessibility
- Accessibility in larger cities: slower speeds dissipate most gains from reduced distance
  - If one walks instead of drives, accessibility rises three times faster with city population.
- Two factors explain most of the speed-distance trade-off:
  1. Crowding: Cities with more people, or less area have shorter distances but slower travel.
  2. Location choice: People live further from venues when speeds are faster.

Why it's Important

- Cities exist to reduce distance between people and facilitate interactions.
  - Accessibility is the raison d'être of cities.
- Motorized road travel accounts for most trips worldwide
  - Important to understand the trade-off it generates as an urban transportation technology.
- We lack accessibility measures that are comparable between cities and countries.
  - Limits policymaker's ability to benchmark performance.

Roadmap

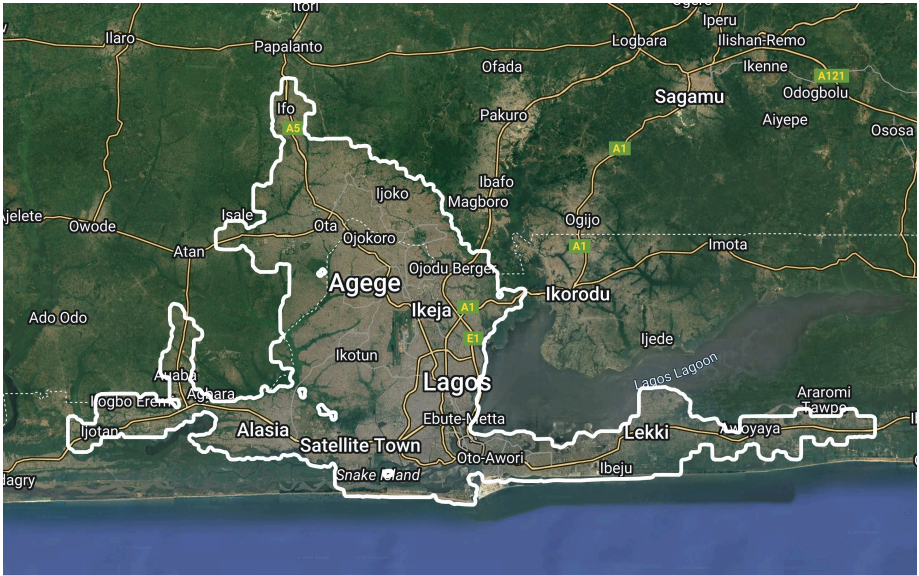
1. Data
2. Measuring Accessibility
3. Documenting and Explaining the Speed-Distance Trade-off
4. Impact of Speed-Distance Trade-off on Accessibility

Data

Delineating Cities

- City *points*: All 1,860 cities with projected 2018 population over 300,000
  - Data from UN World Urbanization Prospects
- City *boundaries*: Defined using GHS-SMOD 1-km layer circa 2015.
  - After various corrections (e.g., merges), 1807 cities remain
- Drop China and South Korea due to restrictions on Google Maps
  - 1,358 cities remain

Illustration: City Boundary vs. Satellite Map of Lagos, Nigeria



Measuring Speed: Trip Sampling on Google Maps.

- Information on speed comes from 900M simulated "real-time traffic" motor vehicle trips.
  - Same Google Maps data as in Akbar, Couture, Duranton, Storeygard (2023a)
- Google reports distance and time on recommended route.
- Google also reports time in hypothetical state of no traffic (uncongested speed)
- We discuss representativeness and accuracy of this data in Akbar et al. (2023a, 2023b).

Measuring Distance to Venues: Sampling of Google Places

- Information on distance to destinations comes from Google Places.
- Google Places data comes from a variety of sources.
  - Business owners have incentives to add their venue to Google Places.
- We searched Google Places using 4000+ keywords in every sample city.
  - Keywords ("Restaurant", "Police Station") selected to cover universe of trip destinations.
  - We searched across all areas of each city until every keyword stops returning new venues.
  - We identified 89 million unique venues across all cities.

Measuring distance: Categorization of Google Places Venues

- We assign each venue to one of 97 types using their Google Places labels.
  - Almost all these types are defined by Google (e.g., clothing store, post office)

- We aggregate 60 out of 97 types into 15 categories:
  - Bank, Broad Retail, Destination Venues, Doctor, Entertainment, Government Services, Grocery, Hospital, Offices and Business Services, Personal Care Services, Religion and Community Center, Restaurant, School, Specialized Retail, Transit
  - These categories account for 73 percent of venues.
  - We use the remaining 38 types in robustness checks.

Comparing our Google Places Sample to Alternative Venue Data

- Universe of venues on Google Places.
  - In 1200 cities, we collected our main sample of Google Places venue (low cost)
  - In 114 cities, we used Google's API to collects the universe of venues (high cost)
  - Correlation of 0.99 between distance indices from Google sample vs universe ⏩ Closest ⏩ Variety

- Mexican Census, 2022, Dhaka Survey, 2023, Kampala Survey (for this project, 2023)
  - Google Places has excellent match with Mexican Census, very good with Dhaka.
  - More venues missing in Kampala further from center (lots of informal venues) ⏩ Cities (Mexico) ⏩ Neighborhoods ⏩ Types

Data: Other City Attributes

- *City Size*:
  - Population: *WorldPop* (Population per 90m X 90m pixel)
  - Area: Our city boundaries
- *Infrastructure*:
  - Major road length: *OpenStreetMaps* sum of motorways, primary, secondary, tertiary roads
- Many more attributes available for topography, city shape, etc, not shown today.

Measuring Accessibility

Simplest Accessibility Index: Inverse of Time to Closest Destination.

- An accessibility index is like a price index:
  - Each destination is a good
  - Price of a good is travel time to destination
- We first compute an accessibility index that is:
  - Defined at a given point in space
  - Defined for a given venue type

Simplest Accessibility Index: Inverse of Time to Closest Destination.

- Decompose accessibility into speed and distance:
  - $Distance_{ijk}$ is distance from point i to destination j in venue type k.
  - $Speed_i$ is the average speed of trips originating or ending in point i.
  - $Speed_{ijk} = Speed_i \times Distance_{ijk}^{\beta_S}$ to account for longer trips being faster.

- Simplest accessibility index is (inverse of) travel time to access closest destination:

$$Accessibility_{ik} = \frac{1}{Time_{i1k}} = \frac{Speed_i \times Distance_{i1k}^{\beta_S}}{Distance_{i1k}} = \frac{UncongestedSpeed_i}{Congestion_i \times Distance_{i1k}^{1-\beta_S}}$$

- Special case of "gains from variety" index with infinitely substitutable venues varietygains

Aggregating index over types and categories

- Computing an index for a given category (e.g. school)
  - Average over all types (e.g., elementary, secondary, university, schools), equally weighted.
  - Robustness: weight average by how common venues in each type are.
- Computing an aggregate index overall all categories.
  - Average over all categories, equally weighted.
  - Robustness: weight by trip shares in the United States, or by trip shares in Mexico City.
- Equivalent to assuming Cobb-Douglas utility over types and categories.

Computing accessibility within each neighborhood

- We define a neighborhood as a 1km square.
- How do we sample points i to compute an average index within a neighborhood?
  - Distance to venues: sample 16 locations in each neighborhood.
  - Speed: sample all locations in Akbar et al. (2023) that are either trip origin or destination in that neighborhood.

Computing accessibility within each neighborhood

- Each observation in these regression in an origin-destination pair:

$$\begin{aligned}
\ln \text{UncongestedSpeed}_{ij} &= U_{n(i)} + \beta_U \ln \text{Distance}_{ij} + \gamma_U X_i + \epsilon_{ij} \\
\ln \text{Congestion}_{ij} &= K_{n(i)} + \beta_C \ln \text{Distance}_{ij} + \gamma_C X_i + \epsilon_{ij} \\
\ln \text{Speed}_{ij} &= S_{n(i)} + \beta_S \ln \text{Distance}_{ij} + \gamma_S X_i + \epsilon_{ij} \\
(1 - \hat{\beta}_S) \ln \text{Distance}_{ik} &= D_{n(i)k} + \epsilon_{ik}
\end{aligned}$$

- The neighborhood fixed-effects U_n, K_n, S_n and D_{nk} are our uncongested speed, congestion, speed, and distance indices.
- X_i are factors only affecting speed like weather an time of day.
- We compute accessibility in type k as $A_{nk} = U_n - K_n - D_{nk}$.

Computing accessibility within each city

- City-level indices are population-weighted average of neighborhood-level indices.
- 44% of accessibility variation is across cities, 56% across is neighborhoods (pop weighted)
  - Most speed variation is *across* cities (72%).
  - Most distance variation is *within* cities (68%).

Does exact location of venue and people matter for accessibility?

- Our distance index relies on precise location of venue and people
- Could variation in our distance index be explained simply by venue density in a city?
- For a typical type and country, 33% of the variation in our distance index is unexplained by venue density.
  - In the United States, 45% of is unexplained, so variation in location choice is important.
  - Least related to venue density: embassies, zoos and aquariums, and airports.
  - Most related: corporate office, construction, handyman, child care, laundry, and liquor store

Distance, Neighborhood level

Rank	Neighborhood	Shortest Distance City	Country	Index
1	Garment District	New York	United States	-1.63
2	Central	Hong Kong	Hong Kong, China	-1.61
3	Soho	London	United Kingdom	-1.60
4	Financial District	New York	United States	-1.55
5	Outram	Singapore	Singapore	-1.54
6	Casco Antiguo	Zaragoza	Spain	-1.54
7	NoMad	New York	United States	-1.54
8	Centro	Rio de Janeiro	Brazil	-1.53
9	Holborn	London	United Kingdom	-1.53
10	New Town	Praha (Prague)	Czechia	-1.52
11	L'Antiga Esquerra de l'Eixample	Barcelona	Spain	-1.52
12	Sadashiv Peth	Pune (Poona)	India	-1.52
13	Call de Barcelona	Barcelona	Spain	-1.52
14	Wan Chai	Hong Kong	Hong Kong, China	-1.51
15	Dreta de l'Eixample	Barcelona	Spain	-1.50
16	Centro	Curitiba	Brazil	-1.50
17	Porto Antico	Genova (Genoa)	Italy	-1.50
18	San Nicolás	Buenos Aires	Argentina	-1.50
19	Financial District	San Francisco	United States	-1.50
20	Melbourne Arts Precinct	Melbourne	Australia	-1.50

Distance, City level

	Shortest Distance			Longest Distance		
Rank	City	Country	Index	City	Country	Index
1	Genève	Switzerland	-0.83	Okene	Nigeria	1.29
2	Torino (Turin)	Italy	-0.82	Nnewi	Nigeria	1.06
3	Mumbai	India	-0.80	Sikasso	Mali	1.00
4	Pune (Poona)	India	-0.79	Namangan	Uzbekistan	0.87
5	Ahmadabad	India	-0.79	Songea	Tanzania	0.79
6	Taibei	Taiwan	-0.79	Potiskum	Nigeria	0.74
7	Hong Kong	Hong Kong, China	-0.78	Samarkand	Uzbekistan	0.72
8	Bangalore	India	-0.77	Sokoto	Nigeria	0.72
9	Bologna	Italy	-0.77	Tashkent	Uzbekistan	0.71
10	Chennai (Madras)	India	-0.76	Conakry	Guinea	0.70
11	Genova (Genoa)	Italy	-0.75	Gboko	Nigeria	0.69
12	Bandung	Indonesia	-0.74	Ife	Nigeria	0.67
13	Manila	Philippines	-0.74	Gondar	Ethiopia	0.65
14	Madurai	India	-0.74	Andizhan	Uzbekistan	0.62
15	Cagliari	Italy	-0.74	Gäncä	Azerbaijan	0.58
16	Delhi	India	-0.73	Sumquayit	Azerbaijan	0.58
17	Bhubaneswar	India	-0.73	Perm	Russia	0.58
18	Istanbul	Turkey	-0.72	Port Harcourt	Nigeria	0.56
19	Bruxelles-Brussel	Belgium	-0.72	Asyut	Egypt	0.55
20	Vijayawada	India	-0.72	Mardan	Pakistan	0.52

Speed Ranking, Neighborhood level

	Fastest			Slowest		
Rank	City	Country	Index	City	Country	Index
1	Omaha	United States	0.96	Lagos	Nigeria	-1.68
2	Buffalo	United States	0.88	Lagos	Nigeria	-1.57
3	Minneapolis	United States	0.85	Lagos	Nigeria	-1.54
4	Kansas City	United States	0.83	Lagos	Nigeria	-1.53
5	Detroit	United States	0.81	Lagos	Nigeria	-1.52
6	San Jose	United States	0.80	Dhaka	Bangladesh	-1.50
7	Mission Viejo	United States	0.80	Port Harcourt	Nigeria	-1.49
8	Oklahoma City	United States	0.79	Lagos	Nigeria	-1.46
9	Chicago	United States	0.78	Lagos	Nigeria	-1.42
10	Austin	United States	0.76	Lagos	Nigeria	-1.34
11	Houston	United States	0.76	Kolkata	India	-1.31
12	Virginia Beach	United States	0.76	Lagos	Nigeria	-1.31
13	Baltimore	United States	0.74	Lagos	Nigeria	-1.29
14	Kansas City	United States	0.73	Lagos	Nigeria	-1.29
15	Sacramento	United States	0.73	Lagos	Nigeria	-1.28
16	Melbourne	Australia	0.73	Dhaka	Bangladesh	-1.28
17	Greensboro	United States	0.73	Karachi	Pakistan	-1.28
18	Flint	United States	0.72	Lagos	Nigeria	-1.27
19	Chicago	United States	0.72	Port Harcourt	Nigeria	-1.27
20	Columbus, Ohio	United States	0.72	Dhaka	Bangladesh	-1.21

Speed Ranking, City level

	Fastest			Slowest		
Rank	City	Country	Index	City	Country	Index
1	Flint	United States	0.41	Dhaka	Bangladesh	-0.57
2	Greensboro	United States	0.41	Arrah	India	-0.54
3	Wichita	United States	0.40	Ikorodu	Nigeria	-0.52
4	Memphis	United States	0.39	Bihar Sharif	India	-0.52
5	Tulsa	United States	0.39	Lagos	Nigeria	-0.52
6	Kansas City	United States	0.35	Aba	Nigeria	-0.51
7	Knoxville	United States	0.35	Bhiwandi	India	-0.50
8	Bakersfield	United States	0.35	Mymensingh	Bangladesh	-0.50
9	Shreveport	United States	0.35	Manila	Philippines	-0.49
10	Youngstown	United States	0.35	Shillong	India	-0.48
11	Palm Bay-Melbourne	United States	0.35	Cabuyao	Philippines	-0.47
12	Detroit	United States	0.35	Khulna	Bangladesh	-0.46
13	Lansing	United States	0.34	Aizawl	India	-0.46
14	Rockford	United States	0.34	Mombasa	Kenya	-0.46
15	Port St. Lucie	United States	0.34	Bacoor	Philippines	-0.44
16	Toledo	United States	0.34	Phnom Penh	Cambodia	-0.44
17	Fort Worth	United States	0.34	Chittagong	Bangladesh	-0.44
18	Dayton	United States	0.34	Mumbai	India	-0.44
19	Oklahoma City	United States	0.34	Kolkata	India	-0.43
20	Grand Rapids	United States	0.33	Darbhanga	India	-0.43

Accessibility Ranking, Neighborhood level

Rank	Neighborhood	Shortest Time (best accessibility) City	Country	Index
1	Outram	Singapore	Singapore	1.62
2	Downtown Seattle	Seattle	United States	1.60
3	Umhlanga Ridge	Durban (Ethekwini)	South Africa	1.59
4	East Village	San Diego	United States	1.54
5	Harbour	Durban (Ethekwini)	South Africa	1.53
6	Downtown Detroit	Detroit	United States	1.52
7	Millers Point	Sydney	Australia	1.52
8	Central	Hong Kong	Hong Kong, China	1.49
9	Centro	Florianópolis	Brazil	1.49
10	Little Italy	San Diego	United States	1.48
11	Cape Town City Centre	Cape Town	South Africa	1.47
12	Central Business District	Houston	United States	1.47
13	City Center District	Dallas	United States	1.46
14	Cortez Hill	San Diego	United States	1.46
15	Norrmalm	Stockholm	Sweden	1.45
16	Northbridge	Perth	Australia	1.45
17	Korkutreis	Ankara	Turkey	1.45
18	Conceicao	Campinas	Brazil	1.44
19	Pike Pine Retail Core	Seattle	United States	1.44
20	Tanjong Pagar	Singapore	Singapore	1.43

Accessibility Ranking, City level

	Shortest Time (best accessibility)			Longest Time (worse accessibility)		
Rank	City	Country	Index	City	Country	Index
1	Cagliari	Italy	0.83	Okene	Nigeria	-1.25
2	Bilbao	Spain	0.80	Sikasso	Mali	-1.14
3	Modena	Italy	0.80	Nnewi	Nigeria	-0.94
4	Hong Kong	Hong Kong, China	0.79	Conakry	Guinea	-0.93
5	Torino (Turin)	Italy	0.78	Songea	Tanzania	-0.89
6	Parma	Italy	0.77	Namangan	Uzbekistan	-0.78
7	Vicenza	Italy	0.77	Ife	Nigeria	-0.76
8	Bari	Italy	0.77	Gondar	Ethiopia	-0.74
9	Salerno	Italy	0.76	Samarkand	Uzbekistan	-0.73
10	Bologna	Italy	0.76	Asyut	Egypt	-0.73
11	Lisbon	Portugal	0.75	Mbeya	Tanzania	-0.73
12	Pescara	Italy	0.73	Potiskum	Nigeria	-0.72
13	Basel	Switzerland	0.73	Maiduguri	Nigeria	-0.67
14	Valencia	Spain	0.73	Gboko	Nigeria	-0.67
15	Verona	Italy	0.72	Port Harcourt	Nigeria	-0.66
16	Brasília	Brazil	0.72	Sokoto	Nigeria	-0.66
17	Istanbul	Turkey	0.71	Peshawar	Pakistan	-0.63
18	Brescia	Italy	0.71	Ikorodu	Nigeria	-0.61
19	Genève	Switzerland	0.70	Az-Zaqazig	Egypt	-0.60
20	Venezia	Italy	0.70	Onitsha	Nigeria	-0.60

Some take-aways

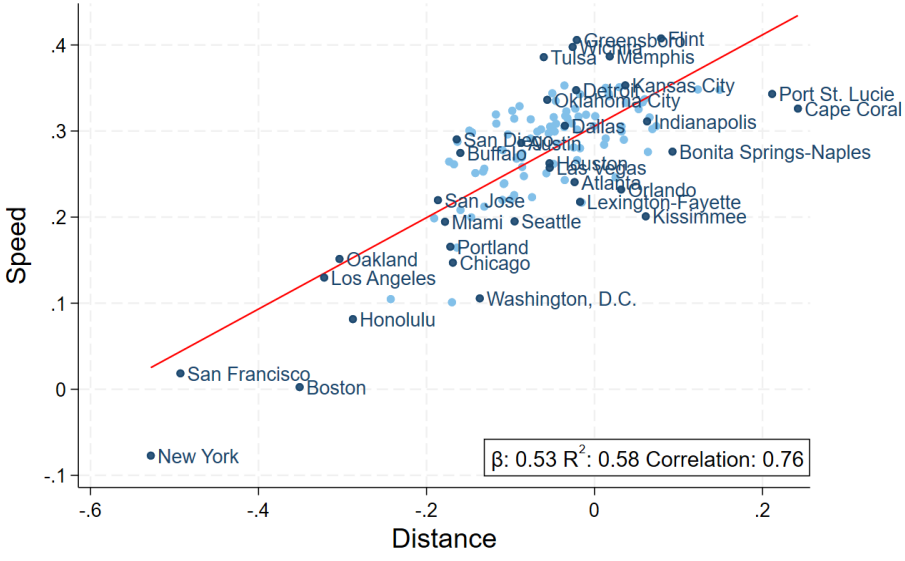
- Importance of short distances: many cities with shortest distances are most accessible
  - Hong Kong, Geneva, Cagliari, Istanbul, Bologna
  - Distance explains about 2.5 times accessibility variance as speed across cities cities
  neighborhoods

- Speed-distance trade-off: some cities with shortest distances to venues are also slowest
  - Mumbai, Manila

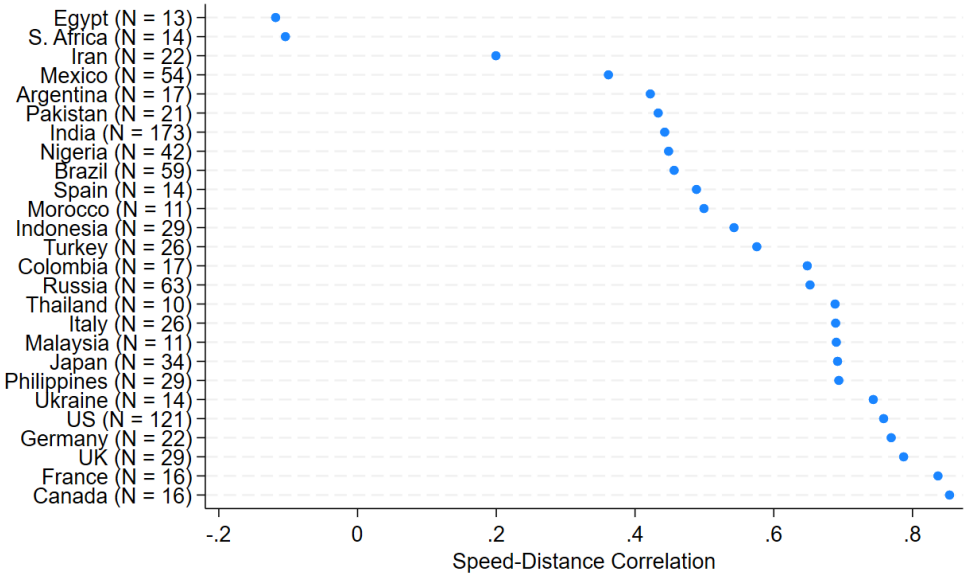
- Gains from variety (not shown):
  - Barely affects ranking, unless elasticity of substitution as low as Su 2023 finds for museums
  - In that case, Singapore and Hong Kong become most accessible cities.

Documenting and Explaining the Speed-Distance Trade-off

The Speed-Distance Trade-off: Cities in the United States.



The Speed-Distance Trade-off: Speed-Distance Correlations across Cities.



The Speed-Distance Trade-off: Additional results

- We also find a speed-distance trade-off across neighborhoods within a city.
  - Noisier, speed-distance correlation of 0.31 across neighborhoods within median city.

- Uncongested speed and congestion both matter in generating speed-distance trade-off.
  - Using the $S = U - K$ decomposition, uncongested speed accounts for 58% of the relationship between distance and speed across cities, and 40% within cities. City level

City level (US only) Neighborhood level

Impact of Speed-Distance Trade-off on Accessibility

Impact of Speed-Distance Trade-off on Accessibility Across Cities

	Accessibility	Speed	Distance
(log) City Population	0.08***	-0.16***	-0.25***
	(0.01)	(0.01)	(0.02)
(log) City Area	-0.35***	0.07***	0.43***
	(0.02)	(0.01)	(0.02)
(asinh) Road Length	0.26***	0.08***	-0.18***
	(0.02)	(0.01)	(0.02)
Country FEs	✓	✓	✓
N	1,119	1,119	1,119
Within R^2	0.44	0.35	0.53

- Larger city population raises accessibility (0.08), all else equal.
- Trade-off: speed loss dissipates most of shorter distance gains: -0.16–0.25 = 0.08

Impact of Speed-Distance Trade-off on Accessibility Across Cities

	Accessibility	Speed	Distance
(log) City Population	0.08***	-0.16***	-0.25***
	(0.01)	(0.01)	(0.02)
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	(0.02)	(0.01)	(0.02)
Country FEs	✓	✓	✓
N	1,119	1,119	1,119
Within R^2	0.44	0.35	0.53

- Larger land area reduces accessibility (-0.35), all else equal.
- Trade-off: wider area raises speed (0.07) but not enough to compensate for longer distances to venues (0.43).

Impact of Speed-Distance Trade-off on Accessibility Across Cities

	Accessibility	Speed	Distance
(log) City Population	0.08***	-0.16***	-0.25***
	(0.01)	(0.01)	(0.02)
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Country FEs	✓	✓	✓
N	1,119	1,119	1,119
Within R^2	0.44	0.35	0.53

- More major roads raises travel speed (0.08): they are wider and faster road types.
- Major roads improve distance (-0.18): most venue types locate along major roads.
- Major roads alleviate speed-distance trade-off: raises accessibility (0.26) through both speed and distance.

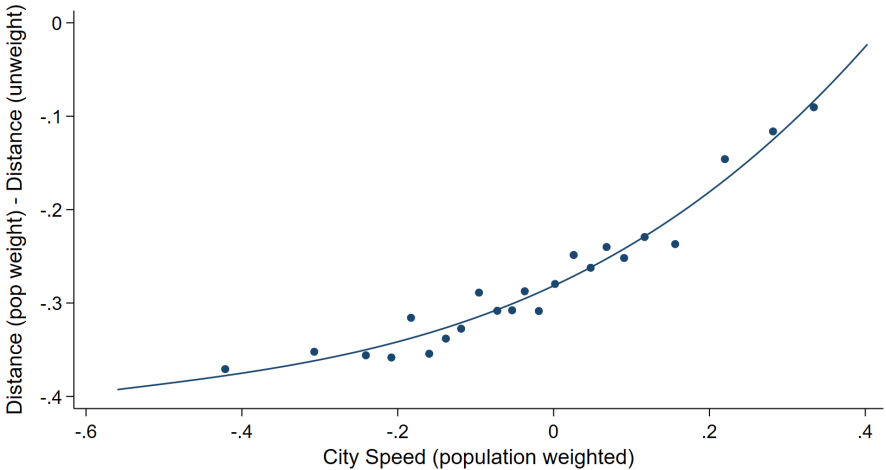
Takeaway

- Accessibility vs population: Slower speeds dissipate most gains from reduced distances.
  - Accessibility-population elasticity for driver: 0.25-0.16=0.08
  - Accessibility-population elasticity for walker: 0.25
- Accessibility vs area: faster speed not enough to compensate for longer distances.
- 'Crowding channel': spatial and population expansion generate a speed-distance trade-off
  - Larger pop: speed (-), distance (+)
  - Wider land area: speed (+), distance (-)
  - Also hold unconditional on road infrastructure.

Location Choice Channel

- Location choice within cities may reinforce the speed-distance trade-off.
- Idea: faster speeds allow people to live farther from venues.
  - E.g., in fast Albuquerque, no correlation between neighborhood population and distance to venues. In slow NYC, people live right on top of venues.
- How do we measure the strength of the location choice channel in a city?
  - Difference between a neighborhood population-weighted and unweighted index.
  - Population weighting distance index captures how people live close to venues.
  - Not weighting (pop. distributed uniformly) assumes venue and people location is unrelated.

Location Choice Channel: Evidence from a binscatter plot.



Binscatter: Each observation is a city, cities from all countries included (N=1105).
Degree 3 fitted polynomial shown.

Explaining the Speed-Distance Trade-off

How important are crowding and location choice channel in explaining the speed-distance trade-off within each country?

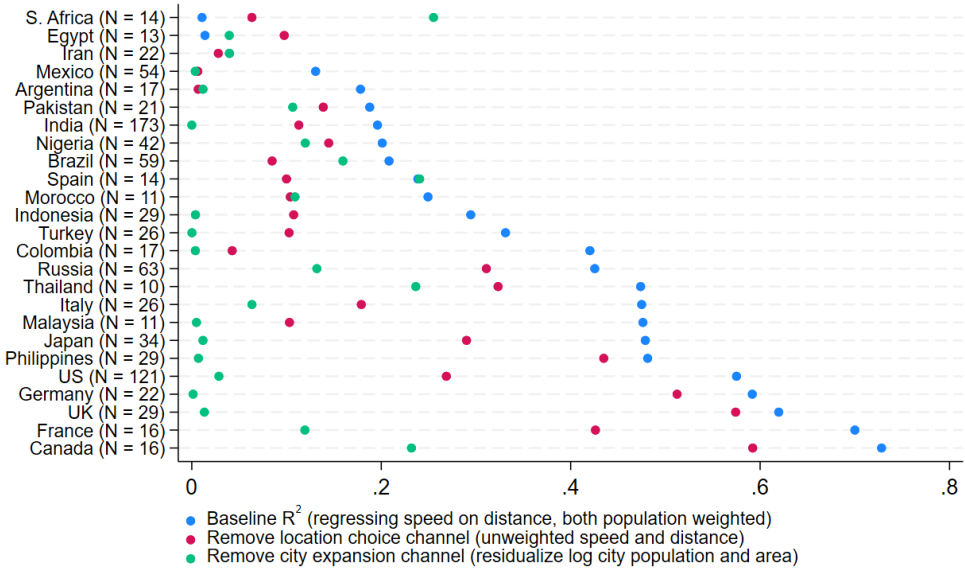
1. *Baseline*: Measure strength of trade-off as R^2 of speed-distance regression.

2. *Removing location choice channel*: R^2 of speed-distance regression, but distance and speed index assume population uniformly distributed within city.

3. *Removing crowding channel*: R^2 of speed-distance, after netting out impact of city population and area i.e., residuals ϵ_c^S and ϵ_c^D in:

$$\text{Speed}_c = \alpha^S + \beta^S \ln(\text{City Pop}_c) + \gamma^S \ln(\text{City Area}_c) + \epsilon_c^S$$
$$\text{Distance}_c = \alpha^D + \beta^D \ln(\text{City Pop}_c) + \gamma^D \ln(\text{City Area}_c) + \epsilon_c^D$$

Can city expansion and location choice explain speed-distance trade-off?



Conclusion

- We showed how to measure accessibility to 100+ venue types in 1000+ cities and 400,000+ neighborhoods.
- We showed that cities with short distances to venues also have slow travel.
  - Due in part to people's location choice preference
  - Due in part to urban crowding: drivers fail to realize most of the gains from larger cities.
  - Congestion only accounts for about half of trade-off, rest is uncongested speed.
  - Road building alleviates speed-distance trade-off

Accessibility with gains from variety

back

- Some venue categories like restaurant feature gains from variety.
- A logit model of travel demand where travels choose destinations based on travel costs delivers a theoretically motivated accessibility index (Ben-Akiva and Lehman)
- Couture (2016) derives such an index that has a CES form:

$$AccessVariety_{ik} = \left(\sum_{j=1}^{J_k} \left(\frac{1}{Time_{ijk}} \right)^{\sigma-1} \right)^{\frac{1}{\sigma-1}}$$

- If we remove gains from variety i.e. as $\sigma \to \infty$, we have that $AccessVariety_{ci}$ tends to simple 'time to closest' venue index.

Accessibility with gains from variety

back

- Taking logs of $AccessVariety_{ik}$:

$$\log(\overline{UncongestedSpeed}_{ik}) - \log(\overline{Congestion}_{ik}) - \frac{1}{1-\sigma} \log \left[\sum_{j=1}^{J_k} Distance_{ijk}^{(1-\beta_S)(1-\sigma)} \right]$$

- So the distance index with variety in neighborhood n, $\bar{V}_n(i)$, comes from the regression:

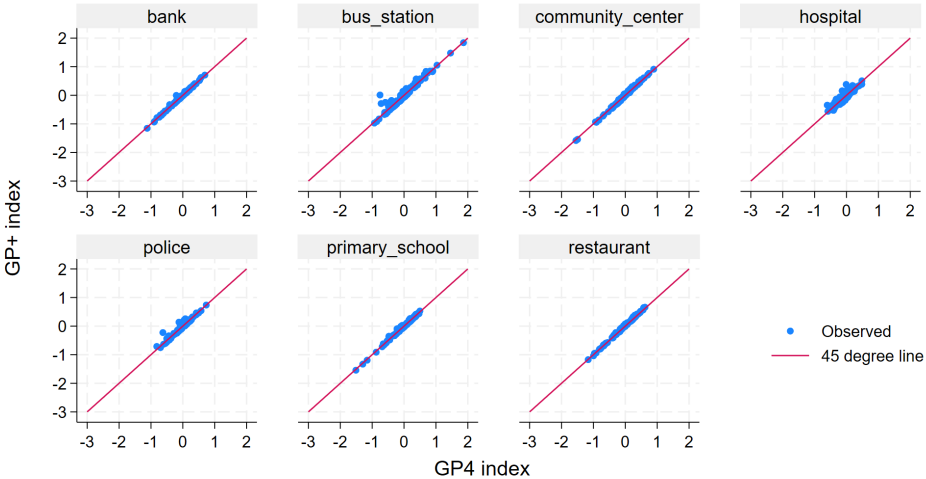
$$\frac{1}{1-\sigma} \log \left[\sum_{j=1}^{J_k} Distance_{ijk}^{(1-\hat{\beta}_S)(1-\sigma)} \right] = \bar{V}_{n(i)k} + \epsilon_{ij}$$

- There are many estimates of σ in the literature.
  - Su (2020) estimates σ for 16 venue categories, ranging from $\sigma = 3.7$ for museums (high gains from variety) to $\sigma = 32.4$ for post offices (almost perfect substitutes).

Accessibility index using Google Sample vs. Universe

back

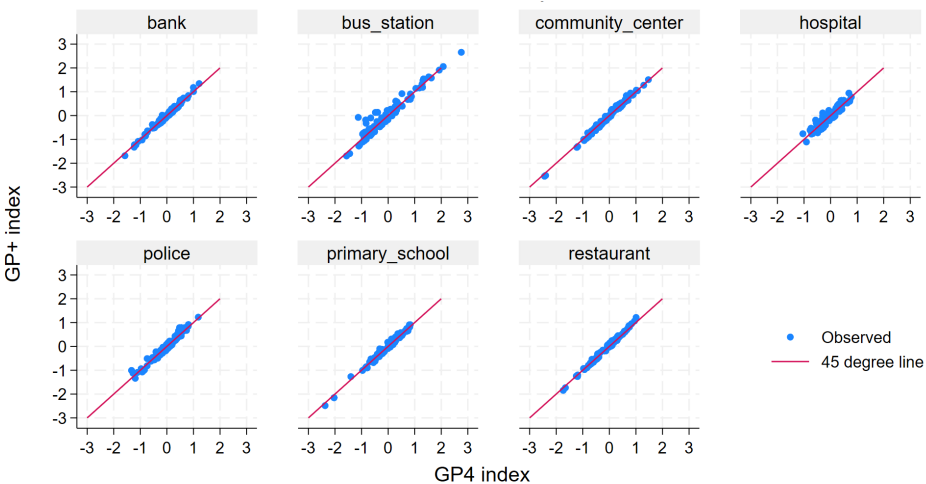
Closest venue



Accessibility index using Google Sample vs. Universe

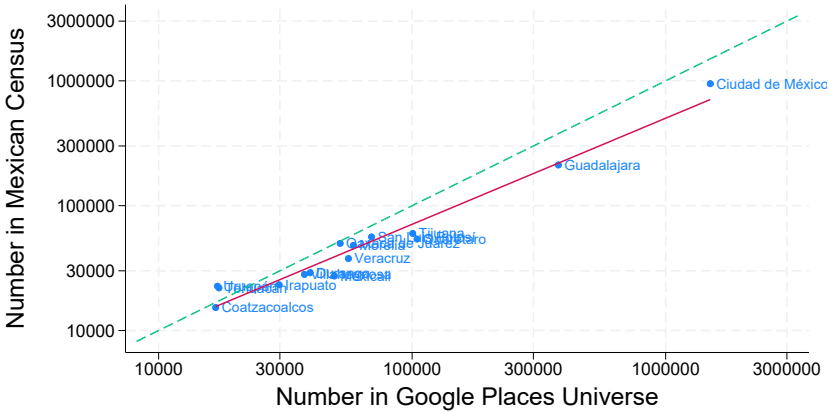
back

Gains from variety, $\sigma = 3$



Log # venues by City, Mexican Census vs. Google Universe

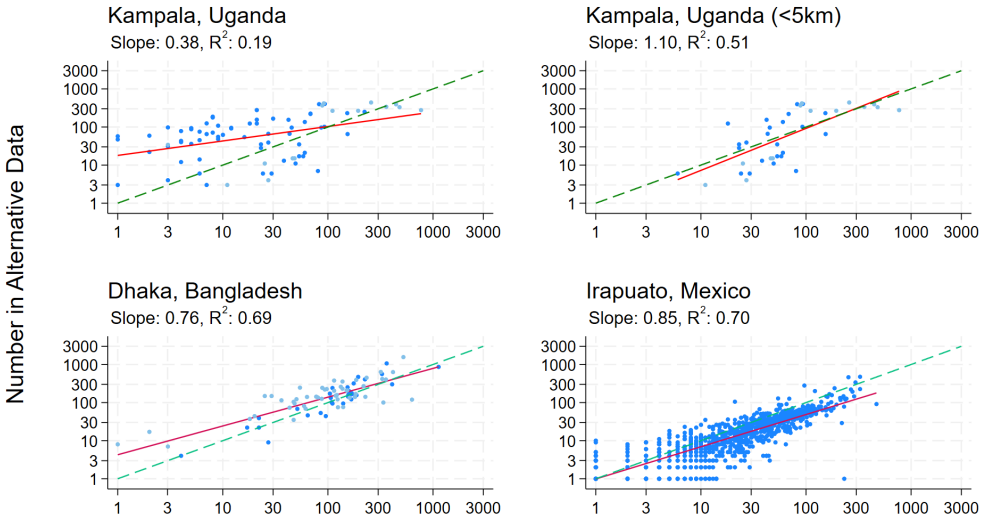
back



Slope: 0.85, R^2: 0.96

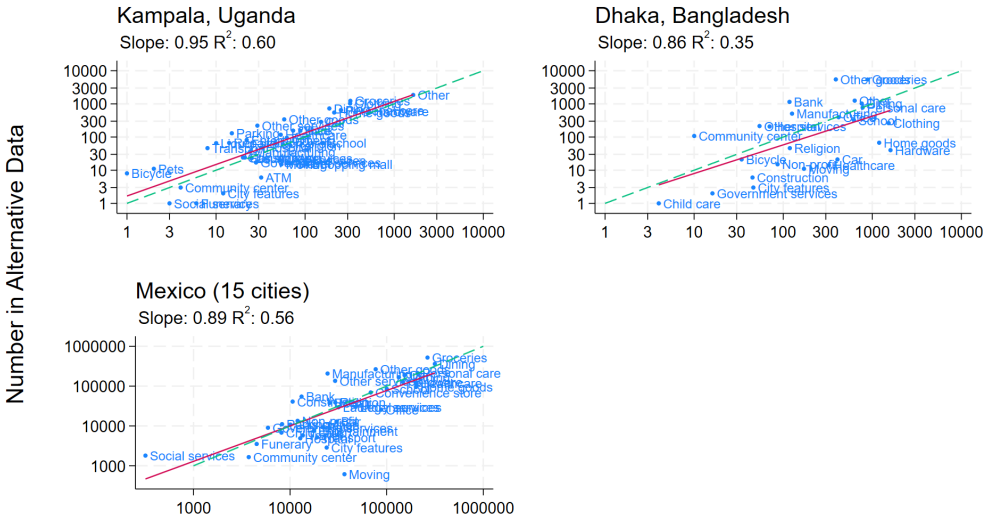
Alternative Data vs. Google Universe: Log # venues by Area

back



Alternative Data vs. Google Universe: Log # venues by Type

back



Uncongested Speed and Congestion in Trade-off, City level

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	Speed	Uncongested Speed	Congestion
Distance	0.26***	0.15***	-0.11***
	(0.02)	(0.02)	(0.01)
Country FEs	✓	✓	✓
N	1,119	1,119	1,119
Within R^2	0.24	0.11	0.38

Uncongested Speed and Congestion in Trade-off, City level (US cities)

back

	Speed	Uncongested Speed	Congestion
Distance	0.53***	0.38***	-0.15***
	(0.06)	(0.04)	(0.02)
N	121	121	121
R^2	0.58	0.53	0.52

Uncongested Speed and Congestion in Trade-off, Neighborhood level

back

	Speed	Uncongested Speed	Congestion
Distance	0.10***	0.04***	-0.06***
	(0.00)	(0.00)	(0.00)
City FEs	✓	✓	✓
N	371,308	371,308	371,308
Within R^2	0.08	0.01	0.27

Variance Decomposition of Accessibility, City level

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	# Cities	Uncongested speed	Congestion	Distance	Cov U-C	Cov U-D	Cov C-D
All cities	1119	0.33	0.02	0.88	0.00	0.07	-0.08
Smallest 50%	560	0.34	0.02	0.91	0.01	0.06	-0.08
Largest 50%	559	0.31	0.02	0.82	-0.00	0.07	-0.07
Largest 10%	111	0.22	0.02	0.77	-0.00	0.01	-0.10

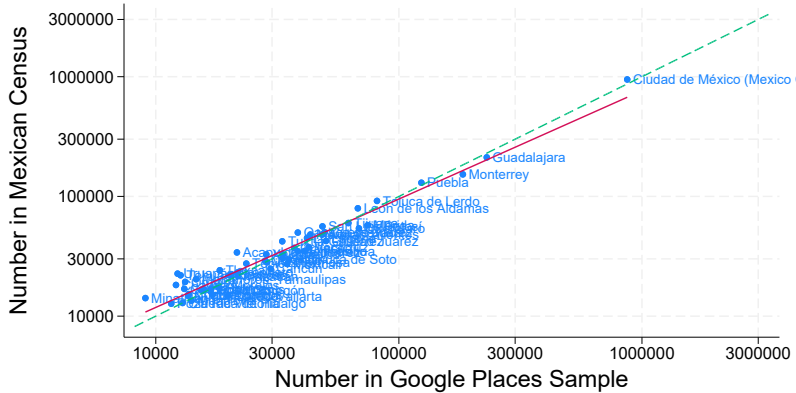
Variance Decomposition of Accessibility, Neighborhood level

back

	# Nhoods	Uncongested speed	Congestion	Distance	Cov U-C	Cov U-D	Cov C-D
All cells	371308	0.24	0.02	0.89	-0.00	0.01	-0.07
Smallest 50%	185654	0.26	0.01	0.59	0.01	-0.11	-0.03
Largest 50%	185654	0.21	0.02	0.93	0.00	0.00	-0.08
Largest 10%	37130	0.19	0.04	0.99	0.00	0.01	-0.11

Mexican Census vs. Google Sample: Log # Venues by City

back

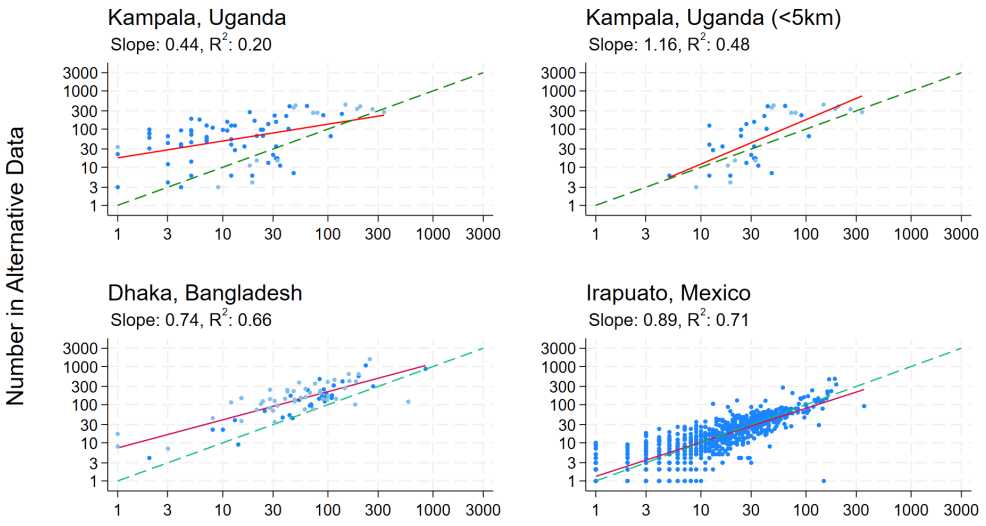


Slope: 0.91, R^2: 0.94

Google Universe

Alternative Data vs. Google Sample: Log # Venues by Area

back Universe



Alternative Data vs. Google Sample: Log # Venues by Type

back Universe

