Aborder la mobilité humaine à travers les traces numériques

Laetitia Gauvin

Institut de Recherche pour le Développement
FRANCE

ISI Foundation

HUMAN MOBILITY IS KEY TO SEVERAL OF THE DEVELOPMENT GOALS

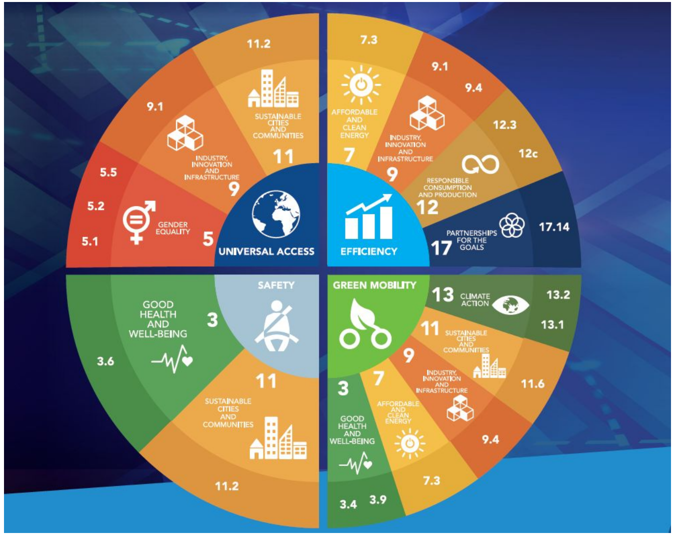
"The world's urban population should grow by 2.5 billion by 2050 (United Nations, 2018)

RAPID URBANIZATION: RETHINKING URBAN MOBILITY

- **Sustainable cities**: analyzing human mobility help to identify areas where to improve accessibility, walkability and user's safety

- **Socioeconomic** and demographic inequalities: Equity in mobility is key to reducing social inequalities as it translates into a more even access to amenities and jobs

- **Health:** Human movement has been shown to play a key role in the dynamics of several pathogens



Source: sum4all

DIGITAL TRACES MORE PRESENT: OPPORTUNITIES & CHALLENGES

- Call Detail Records
- GPS


Source: GoodStudio (Shutterstock)

GENDER & MOBILITY

GENDER AND URBAN MOBILITY

Addressing Unequal Access to Urban Transportation for Women and Girls

GOVLAB
The Governance Lab @ NYU

INSTITUTE
FOR SCIENTIFIC INTERCHANGE
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UDD
Universidad del Desarrollo
Facultad de Ingeniería
Instituto Data Science

unicef

Telefónica
Investigación y Desarrollo Chile

DigitalGlobe™

A project funded by
data2x
partnering for a
gender data revolution

ARE THERE GENDER DIFFERENCES IN MOBILITY?

YES

Women move more!

- chaining trips
- child care
- other activities

Psylla et al. PLOS ONE 2017

YES

Women move less!

- culture, socio-economic factors
- safety concerns
- access to transport

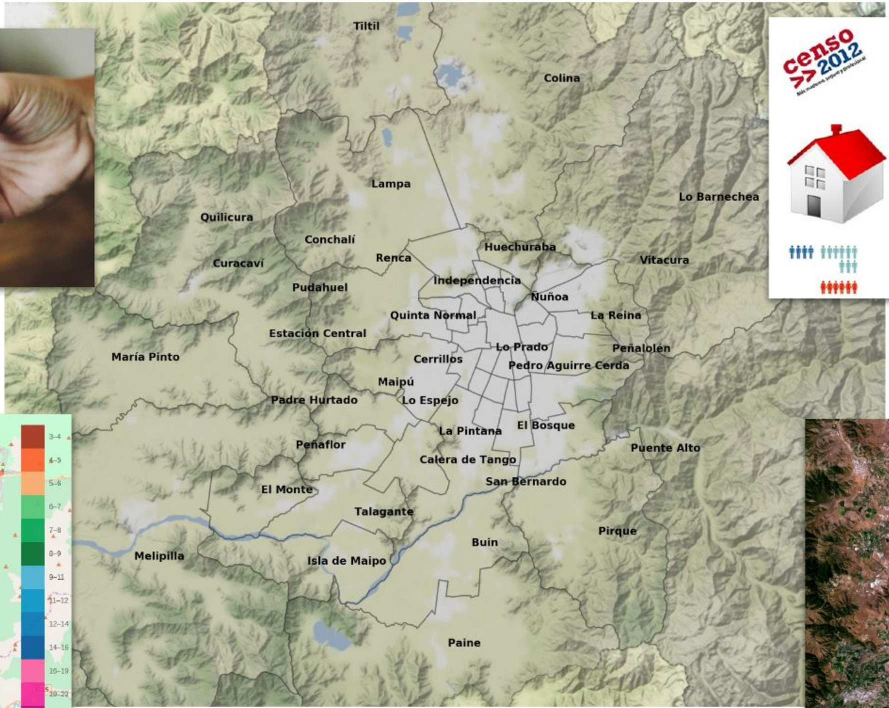
Adeel et al. Transportation 2017

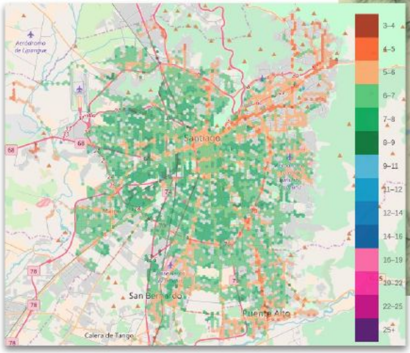
NO

There is no difference!

Song et al. Science 2010

DATA SOURCES





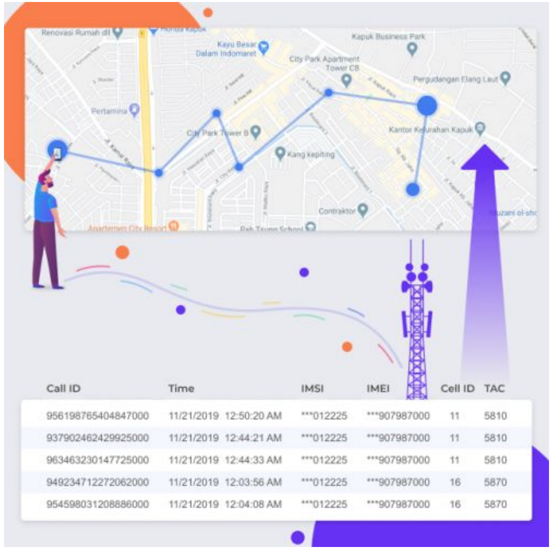
Santiago Metro. Area: ~7 million inhabitants
52 municipalities (Comunas)

WHAT IS CALL DETAIL RECORD (CDR)

A Call Detail Record (CDR) is an accounting record that contains information about how subscribers utilize a phone system. A CDR report provides data about each mobile communication typically includes:

- ➔ Date and time of the call
- ➔ Duration of the call
- ➔ Subscriber phone number
- ➔ Location of cell tower connected
- ➔ Device used

Useful information for a **proxy of mobility**



Source image: https://www.ghtinc.com/what-is-cdr-and-how-does-it-can-help-to-win-the-battle-against-covid-19/

HOME DETECTION

- People tend to have **regular calling patterns**, and certain locations are associated with routine activities such as **home** and **work**
- **Home detection** focuses on **finding these patterns in the CDR** data
- **Typical detection algorithm** is based on **selecting the location of the user during times** of day in which she/he is likely to be at home (usually **night**)
- **Various algorithms**, such as clustering or machine learning models, may be applied to perform this
- The identified home location is usually validated against other data sources (census for instance) or refined using additional data points to increase accuracy.
- Factors such as the frequency of calls, the duration of stay at a location, and movement patterns may be considered to improve the reliability of home detection.

For more details: Evaluation of home detection algorithms on mobile phone data using individual-level ground truth

https://epjdatascience.springeropen.com/articles/10.1140/epjds/s13688-021-00284-9

MOBILE PHONE DATA FILTERING

PERIOD OF STUDY

. June-August 2017 (3 months of activity) / approx. 200 millions calls

USERS SELECTED:

. Only one registered line & Gender information	**770,678** (50.2% F)
. > 1 call per day	**430,079** (51% F)
. Identifiable home locations	**419 ,889** (51.2% F)
. Grupos Socioeconómicos (GSE) labels:	**372152** (50.9% F)

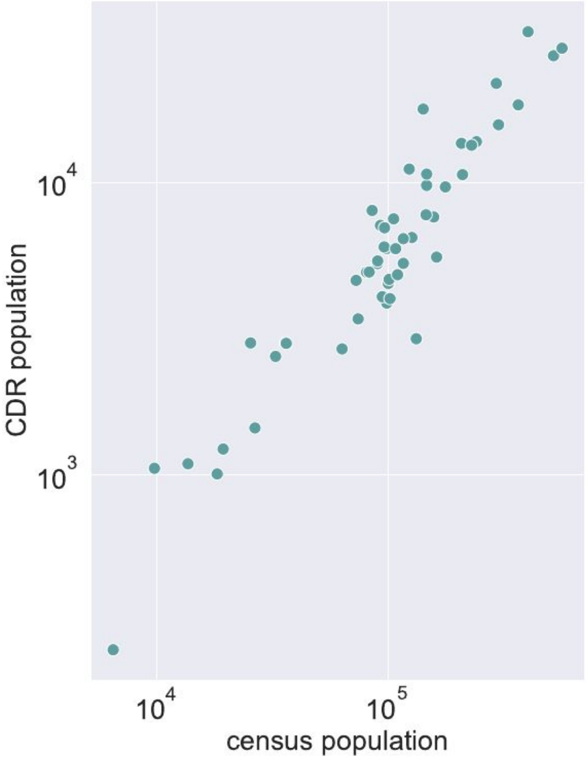
METADATA: SOCIO-ECONOMIC GROUPS

- **AB** *clase alta* ($7,280 monthly average per household)
- **C1a** *clase media acomodada* ($3,436)
- **C1b** *clase media emergente* ($2,280)
- **C2** *clase media típica* ($1,344)

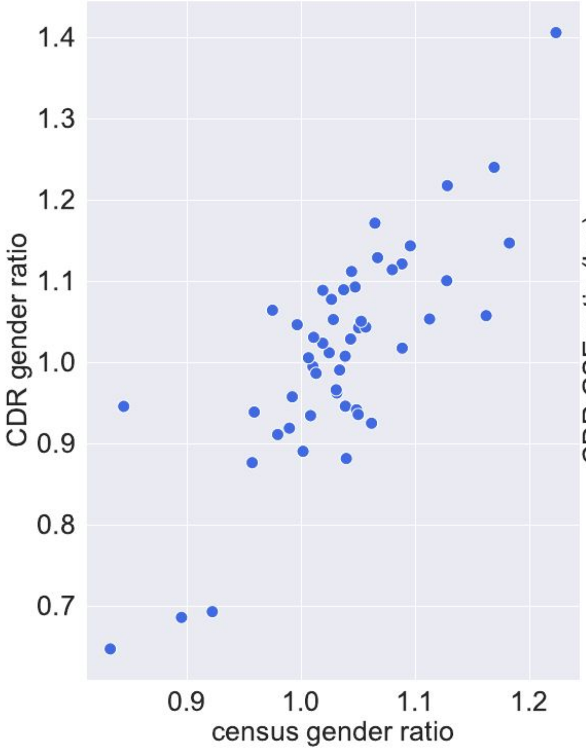
I^* ——— 656,000 Chilean pesos (~1,000 US$)

- **C3** *clase media baja* ($834)
- **D** *vulnerables* ($509)
- **E** *pobres* ($262)

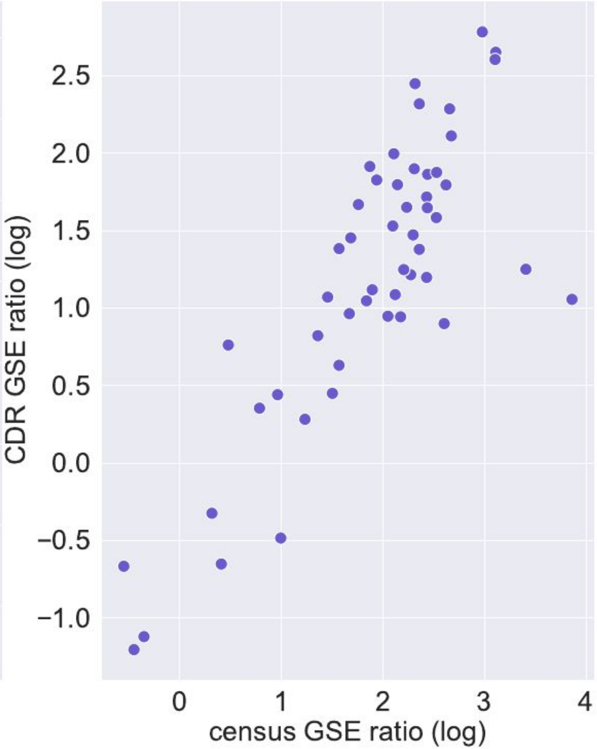
REPRESENTATIVENESS



POPULATION
Pearson Corr. coeff=0.93



GENDER RATIO
Pearson Corr. coeff=0.79



SOCIO-ECONOMIC GROUPS
Pearson Corr. coeff=0.82

SPATIAL MOBILITY METRICS

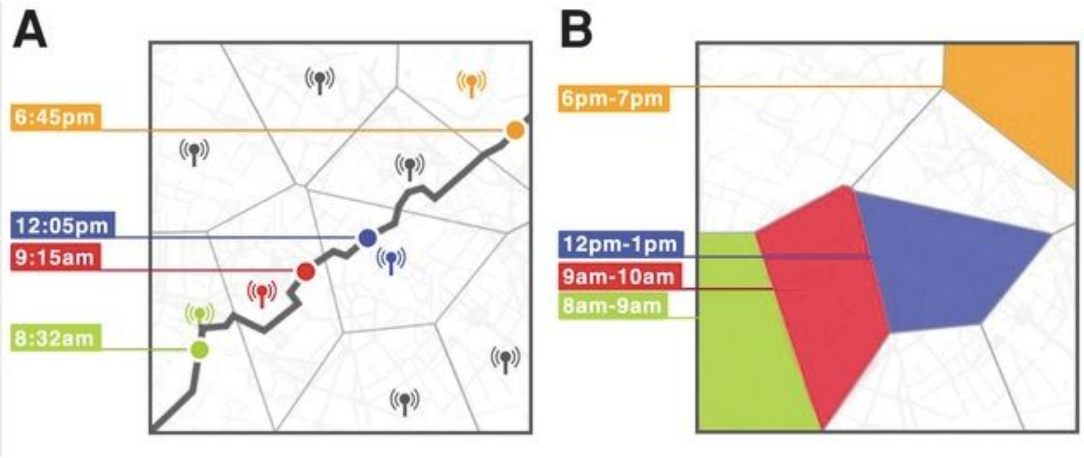
OF UNIQUE VISITED LOCATIONS

$$N_{loc}^{(u)}$$

OF UNIQUE VISITED LOCATIONS

(80% ACTIVITY)

$$N_{loc80}^{(u)}$$



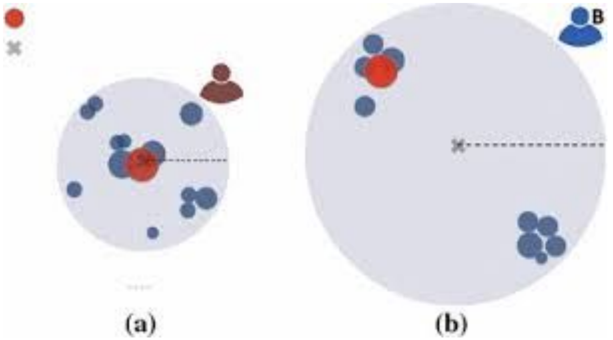
Source image
https://www.wired.com/2013/03/anonymous-phone-location-data/

SPATIAL MOBILITY METRICS

RADIUS OF GYRATION [TYPICAL DISTANCE]

$$R_G = \sqrt{\frac{1}{L}\sum_{i=1}^{L}(\overrightarrow{R_i} - \overrightarrow{R_{cm}})^2}$$

https://www.nature.com/articles/nature06958



Source image
https://link.springer.com/article/10.1007/s41060-016-0013-2-

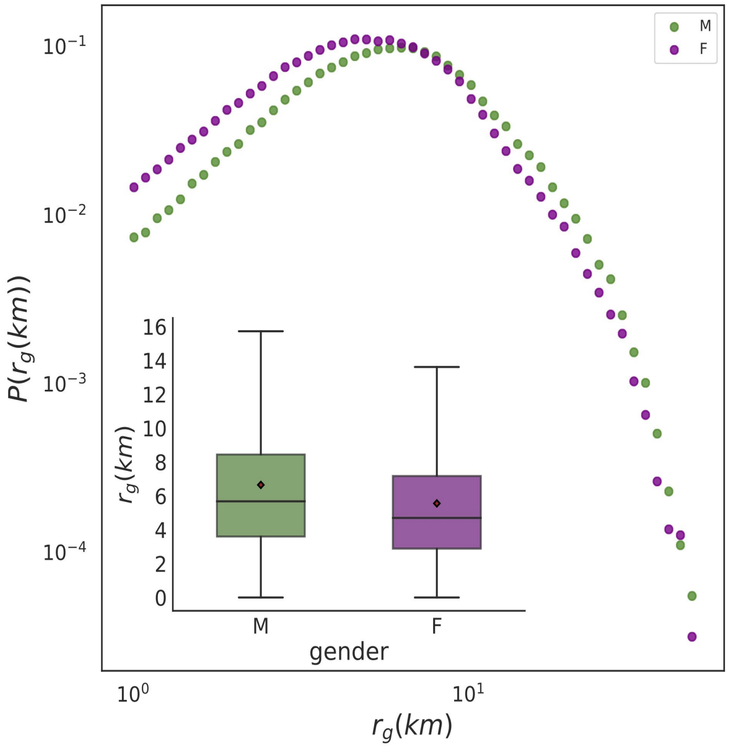
SHANNON ENTROPY [DIVERSITY]

$$S^{(u)} = \sum_i p_i^{(u)} \ln(p_i^{(u)})$$

$p_i^{(u)}$ = *fraction of calls made by u in location i*

https://scikit-mobility.github.io/scikit-mobility/reference/mesures.html

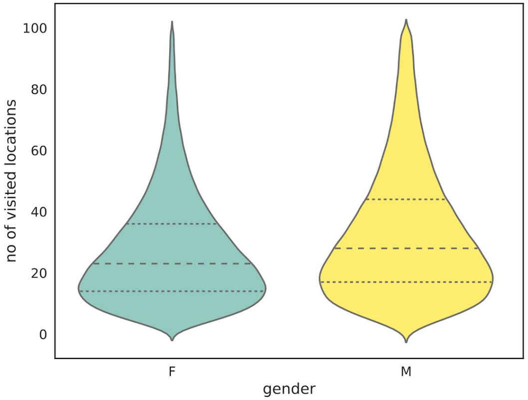
GENDER DIFFERENCES: DISTANCES TRAVELLED

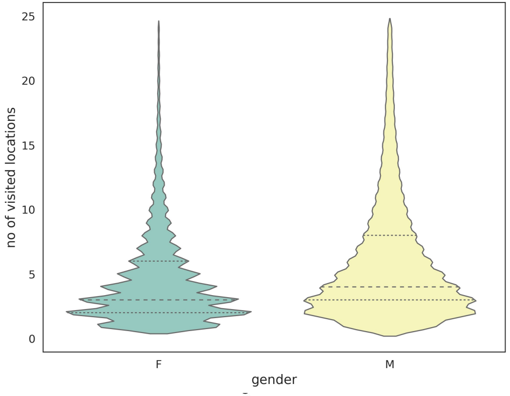


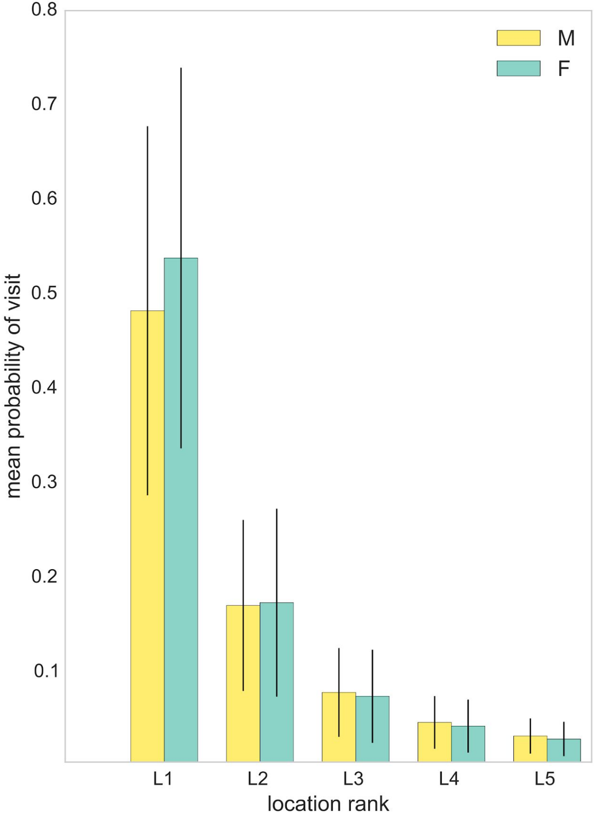
WOMEN TEND
TO STAY IN
SMALLER AREAS

ΔR_G =1.09 [1.07, 1.12]

GENDER DIFFERENCES: # LOCATIONS VISITED







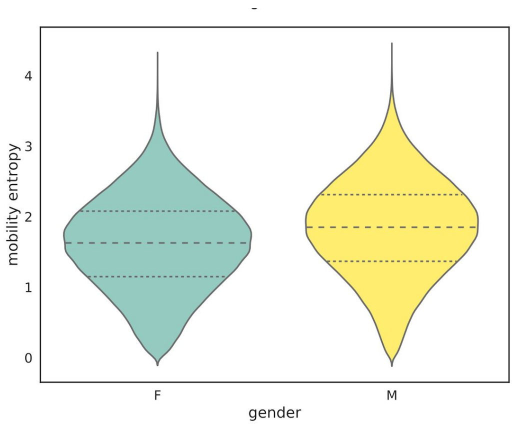
WOMEN

1. ARE MORE LOCALIZED
2. DO LESS TRIPS

$$\Delta N_{loc} = 8.58\ [8.43 - 8.73]$$

$$\Delta N_{loc80} = 2.02\ [1.98 - 2.05]$$

GENDER DIFFERENCES: ENTROPY



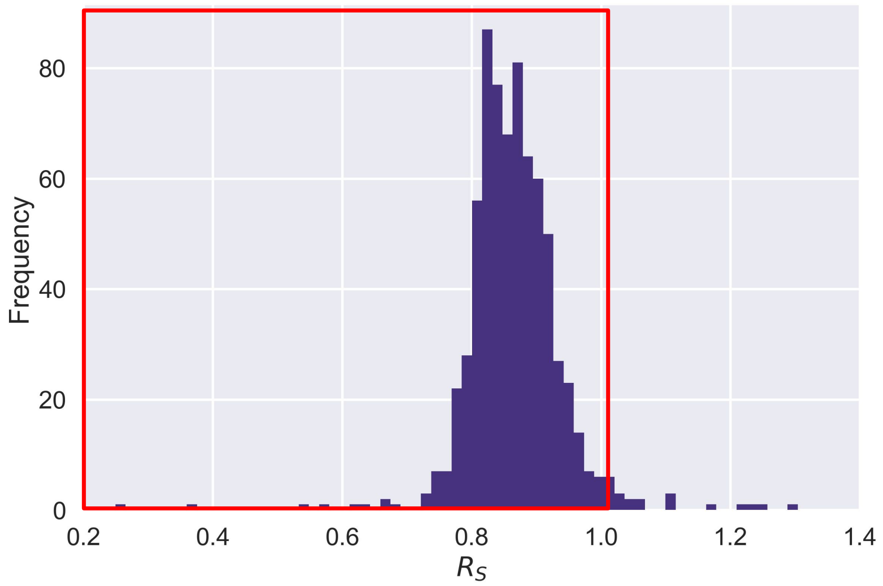
WOMEN'S ENTROPY IS LOWER THAN MEN

ΔS = 0.26 [0.26 - 0.27]

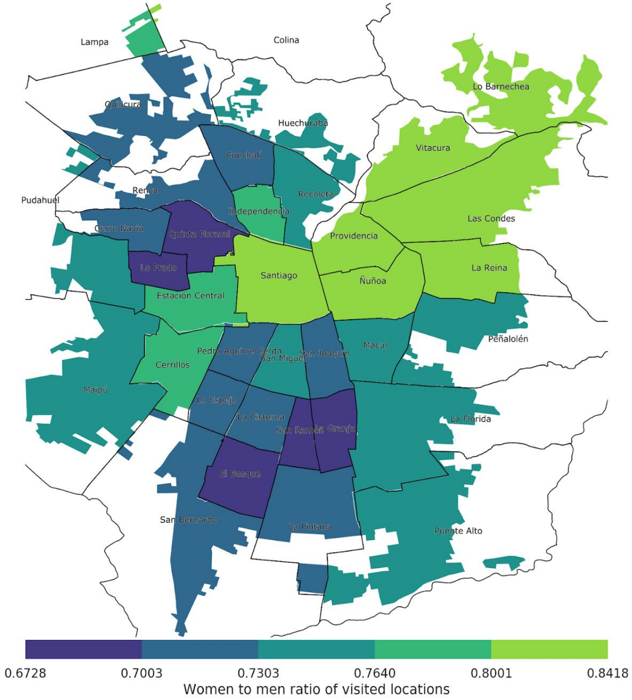
GENDER MOBILITY RATIOS

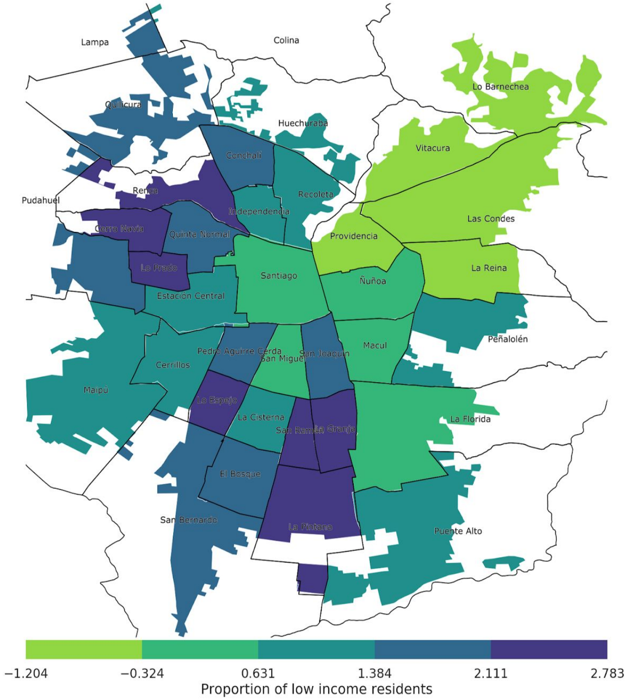
$$R_X(l) \equiv \frac{< X^{(u)} >_{u \in \text{women living at } l}}{< X^{(u)} >_{u \in \text{men living at } l}}$$

$$X^{(u)} = [N^{(u)}_{loc}, N^{(u)}_{loc80}, \ldots]$$



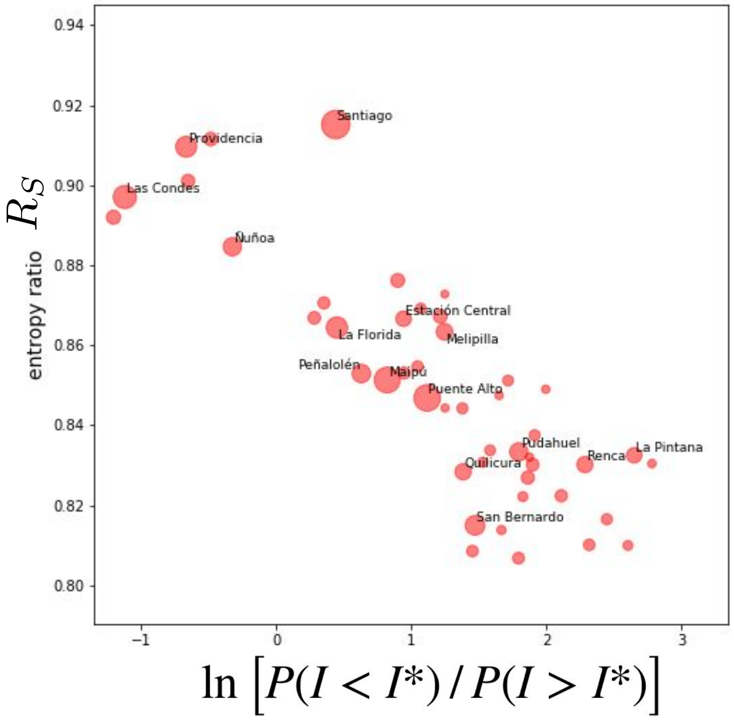
SPATIAL SEGREGATION





Spatial patterns of gender gap in mobility are highly correlated with the spatial patterns of social inequality

SOCIO-ECONOMIC STATUS AND TRAVEL PATTERNS



AS INCOMES INCREASE DIFFERENCES IN TRAVEL BEHAVIOR BETWEEN MEN AND WOMEN DECREASE

GENDER MOBILITY AND SOCIO-ECONOMIC FACTORS

Table 1 Partial correlation values (Pearson) between R_S and $R_{\hat{N}_l}$ and the sociodemographic features of 51 municipalities in the SMR. All correlation values are corrected to take into account differences in calling activity and population distributions by gender.

	R_S	$R_{\hat{N}_l}$
GSE ratio (log)	-0.59***	-0.53***
HDI	0.42**	0.37**
education gender ratio	-0.08	-0.10
employment gender ratio	0.51***	0.37**
fertility rate	-0.53***	-0.40**
couples household	0.55***	0.50***
extended household	-0.61***	-0.57***
family household	-0.30	-0.14
single parent household	-0.32*	-0.32*
single person household	0.56***	0.44**

Controlling for **confounding factors** :

1. gender ratio
2. call ratio

$$\rho_{XY\cdot Z} = \frac{\rho_{XY} - \rho_{XZ}\rho_{ZY}}{\sqrt{1-\rho_{XZ}^2}\sqrt{1-\rho_{ZY}^2}}.$$

ROBUSTNESS ANALYSIS: CALL ACTIVITY VS GENDER GAP

a) Random sampling of the user activity of men : number of calls by men < number of calls by women

50%	25%
Entropy: F 1.7 | M 1.94	Entropy: F 1.7 | M 1.87

Kruskal-Wallis tests significant

b) Random sampling of 200 calls for every user (~72% of the users)

Entropy F: 1.73 M | 2.02

Even when activities are made strictly equal, entropy differences are significant

ROBUSTNESS ANALYSIS: CALL ACTIVITY VS GENDER GAP

c) Regression using the gender and the home call ratio and their interactions as predictors of the entropy

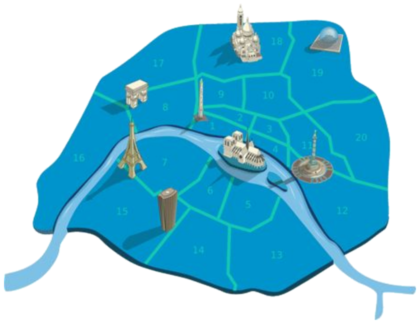
==

	coef	std err
Intercept	1.2148	0.002
gender	-0.0433	0.003
home call ratio	-2.3679	0.004
Interaction home call ratio:gender	0.1774	0.006

R-squared : 0.618

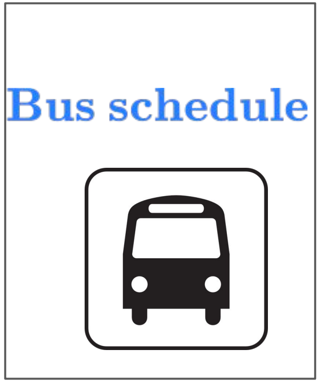
For the same range of home call ratio the entropy of men is higher

DOES PUBLIC TRANSPORTATION ACCESSIBILITY EXPLAIN THE GENDER DIFFERENCES?



spatially embedded

multimodal



time-resolved

GTFS data (open data)

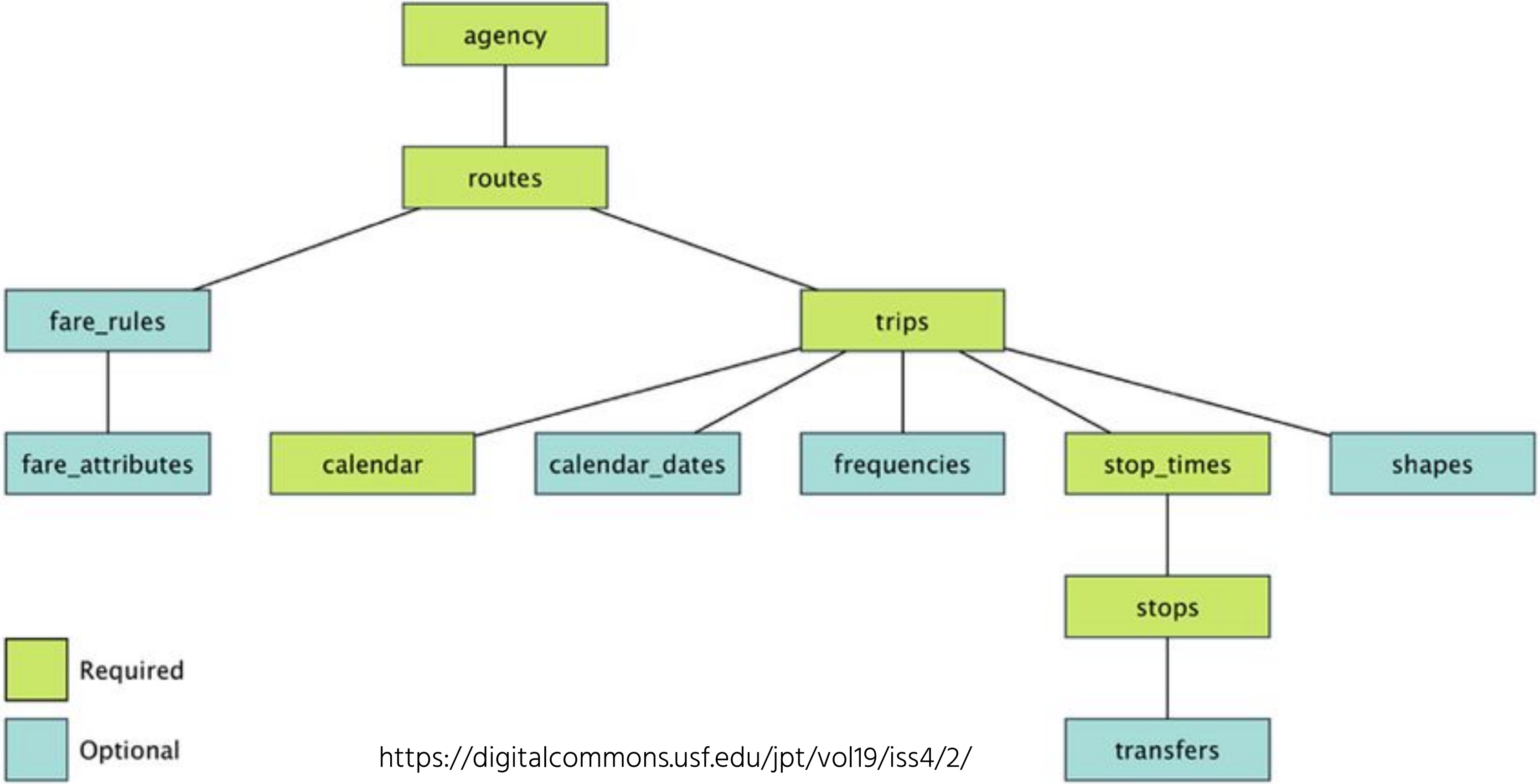
General Transit Feed Specification

geospatial information

&

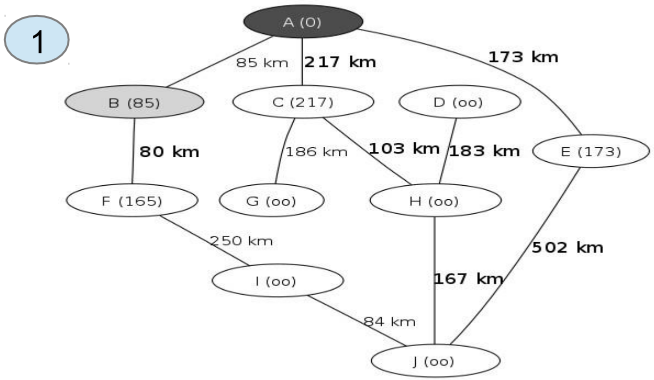
schedule information

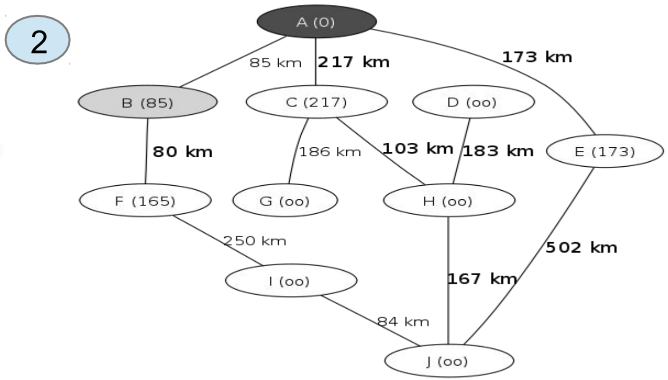
GTFS data (open data)

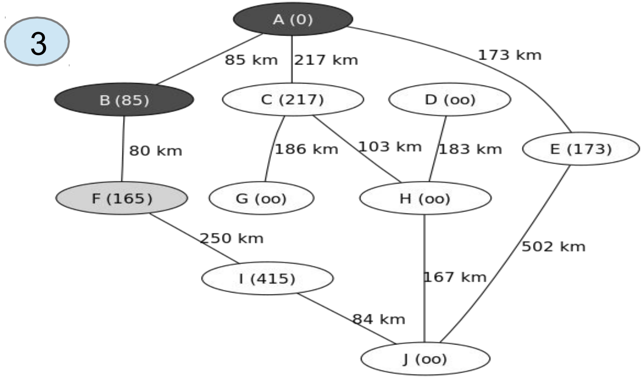


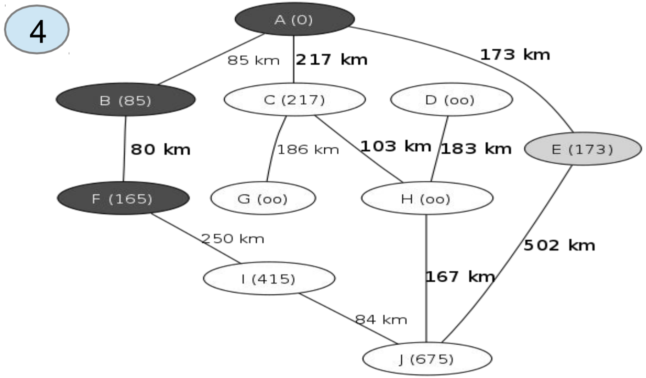
https://digitalcommons.usf.edu/jpt/vol19/iss4/2/

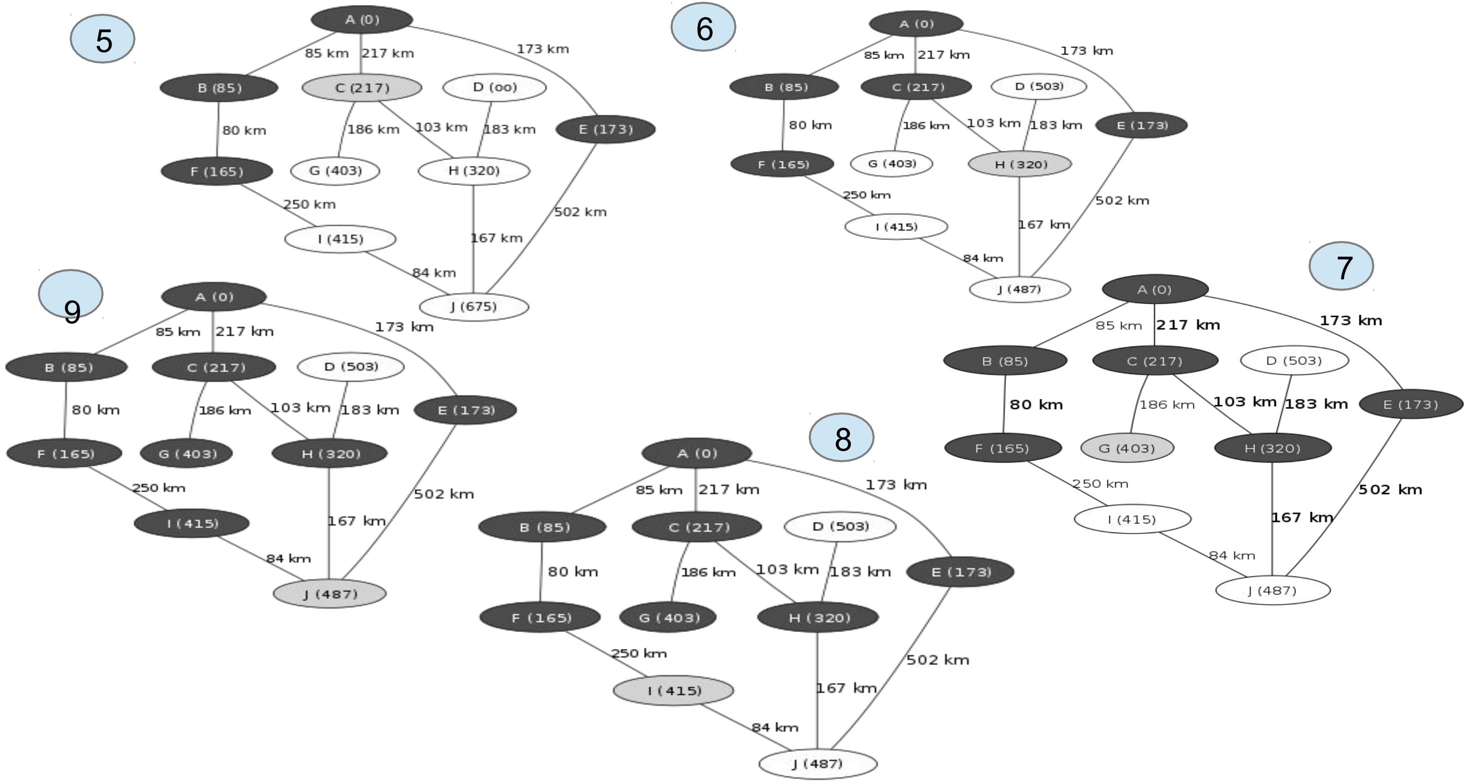
Dijkstra's algorithm











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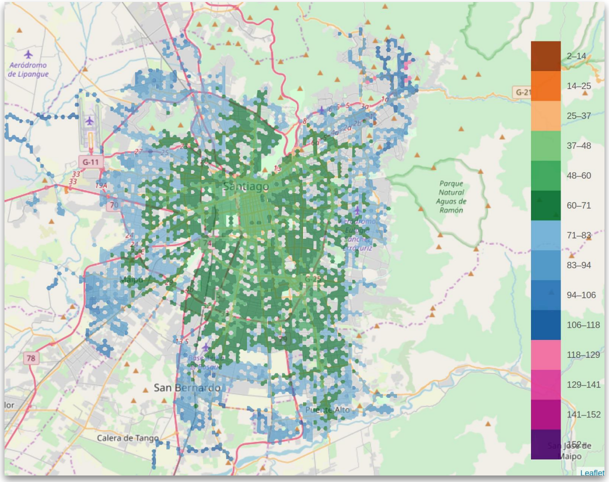
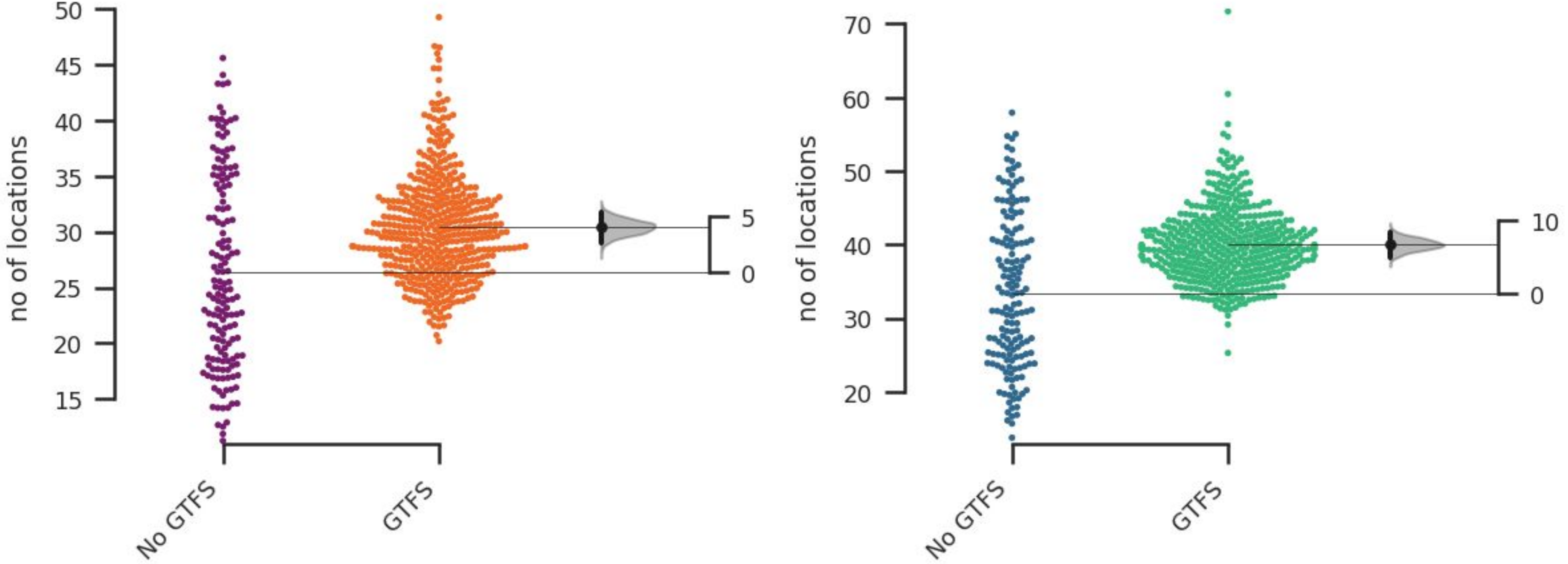
PUBLIC TRANSPORTATION FROM GTFS DATA (OPEN DATA)



TRAVEL TIME

SLIGHTLY NEGATIVE CORRELATIONS WITH THE GENDER GAP

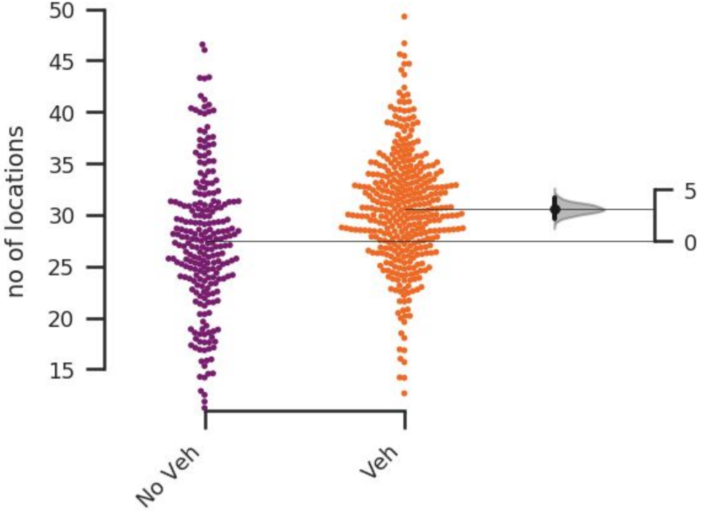
PUBLIC TRANSPORTATION & MOBILITY: ESTIMATION PLOTS

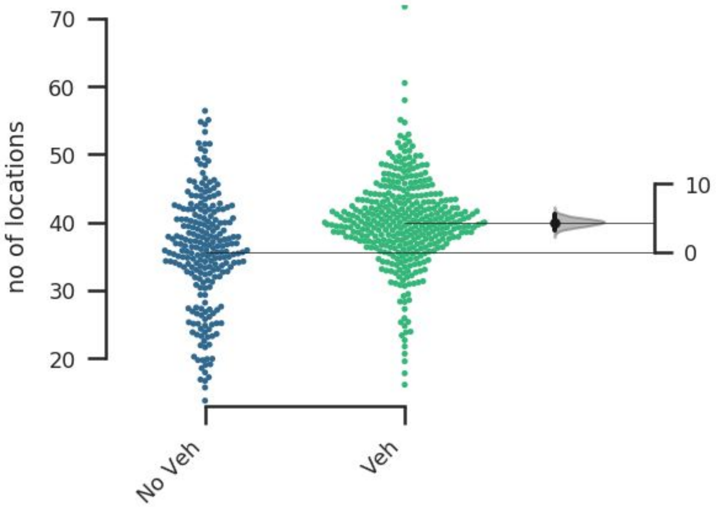


ACCESS TO PUBLIC TRANSPORT INCREASES THE MOBILITY BUT DOES NOT FILL THE GENDER GAP

Ho, J., Tumkaya, T., Aryal, S., Choi, H., & Claridge-Chang, A. (2019). *Moving beyond P values: data analysis with estimation graphics. Nature Methods, 16(7), 565–566.*

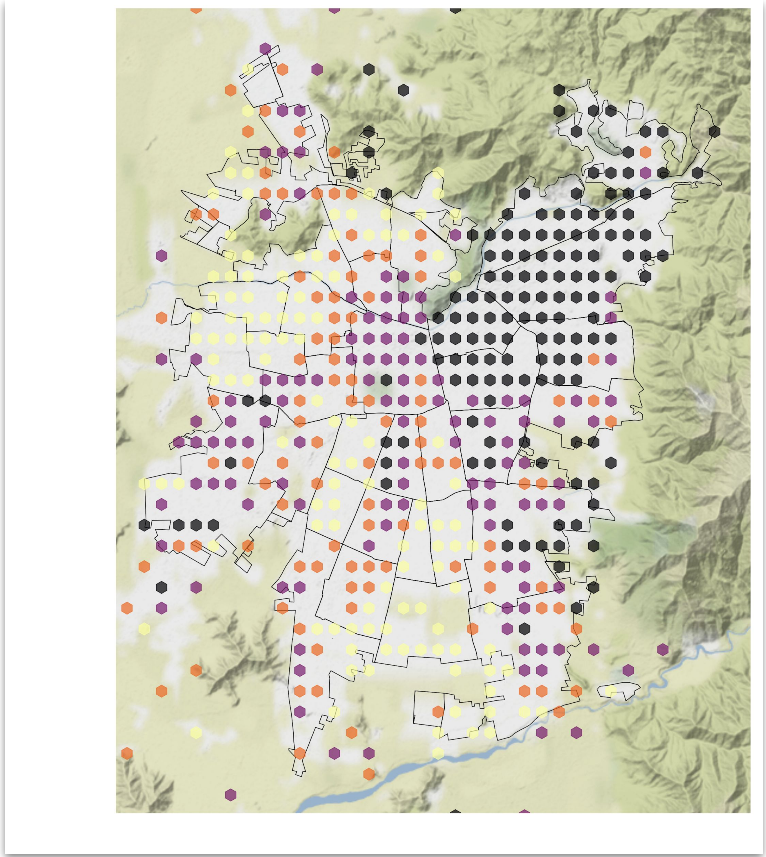
PRIVATE TRANSPORTATION & MOBILITY





ACCESS TO PRIVATE VEHICLE INCREASES THE MOBILITY BUT DOES NOT FILL THE GENDER GAP

SOCIO-ECONOMIC REPARTITION & ACCESS TO TRANSPORTATION



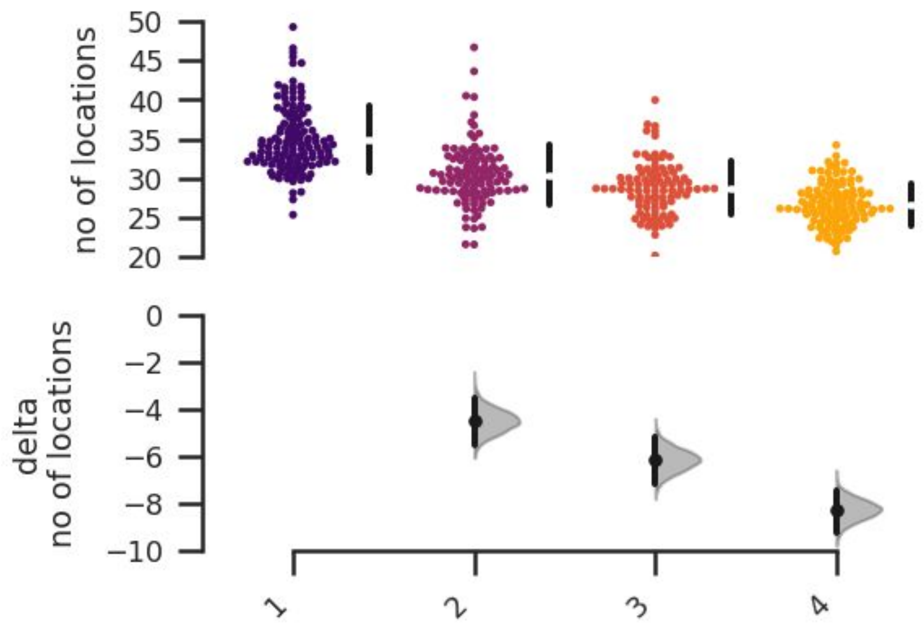
WEALTHIEST

POOREST

WE CLUSTERED THE CELLS BASED ON THE QUARTILES OF THE GSE RATIO

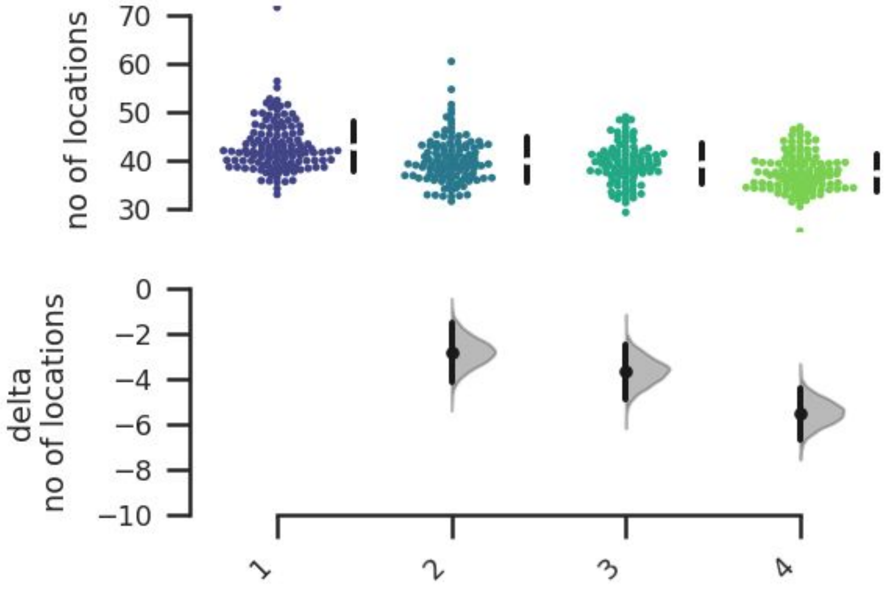
$$P(I < I^*) \,/\, P(I > I^*)$$

PUBLIC TRANSPORTATION & SOCIO-ECONOMIC GROUPS



WOMEN LIVING IN THE POORER AREAS VISIT 8 LOCATIONS LESS THAN THOSE LIVING IN THE RICHER AREAS

PUBLIC TRANSPORTATION & SOCIO-ECONOMIC GROUPS

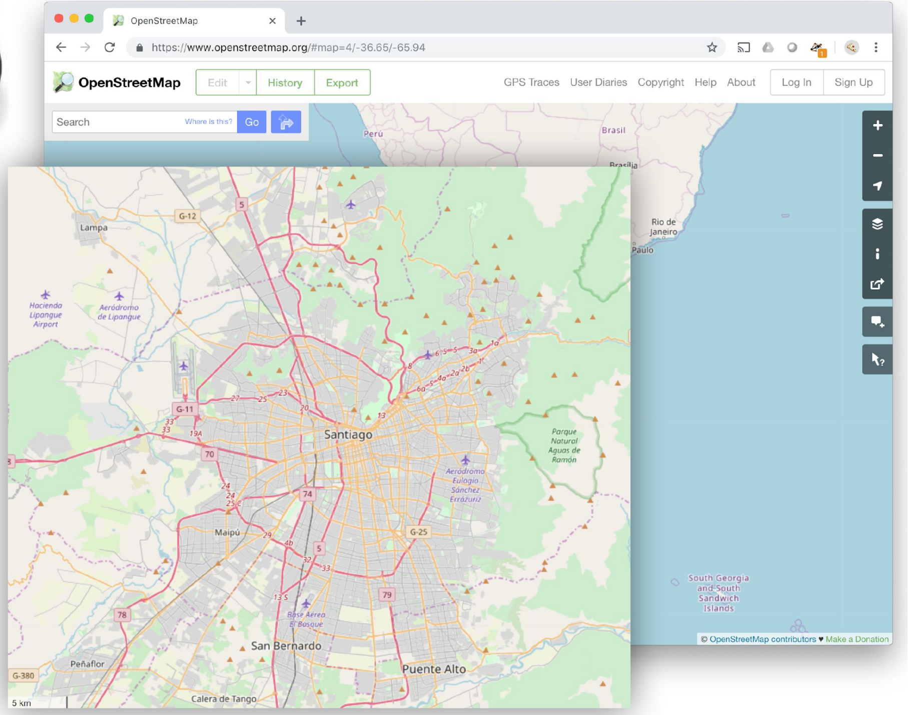


ACCESS TO PUBLIC TRANSPORTATION EQUALIZING MOBILITY ACROSS SOCIO-ECONOMIC SEGMENTS

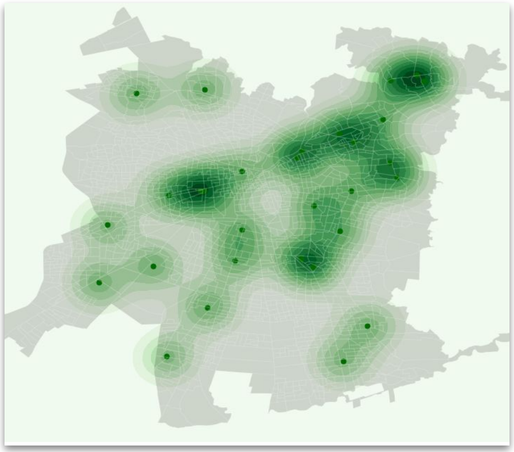
FOR MEN

MAPPING OF THE POINTS OF INTERESTS

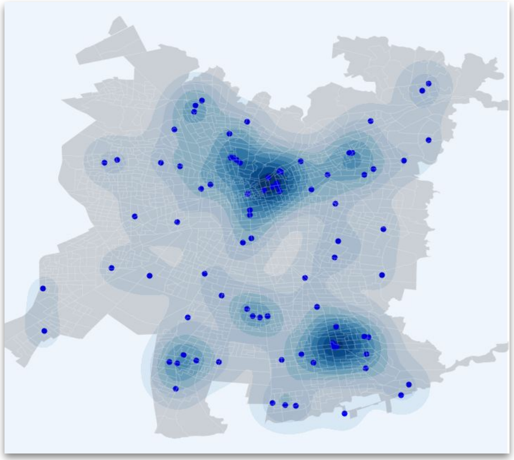
www.OpenStreetMap.org



MAPPING OF THE POINTS OF INTERESTS



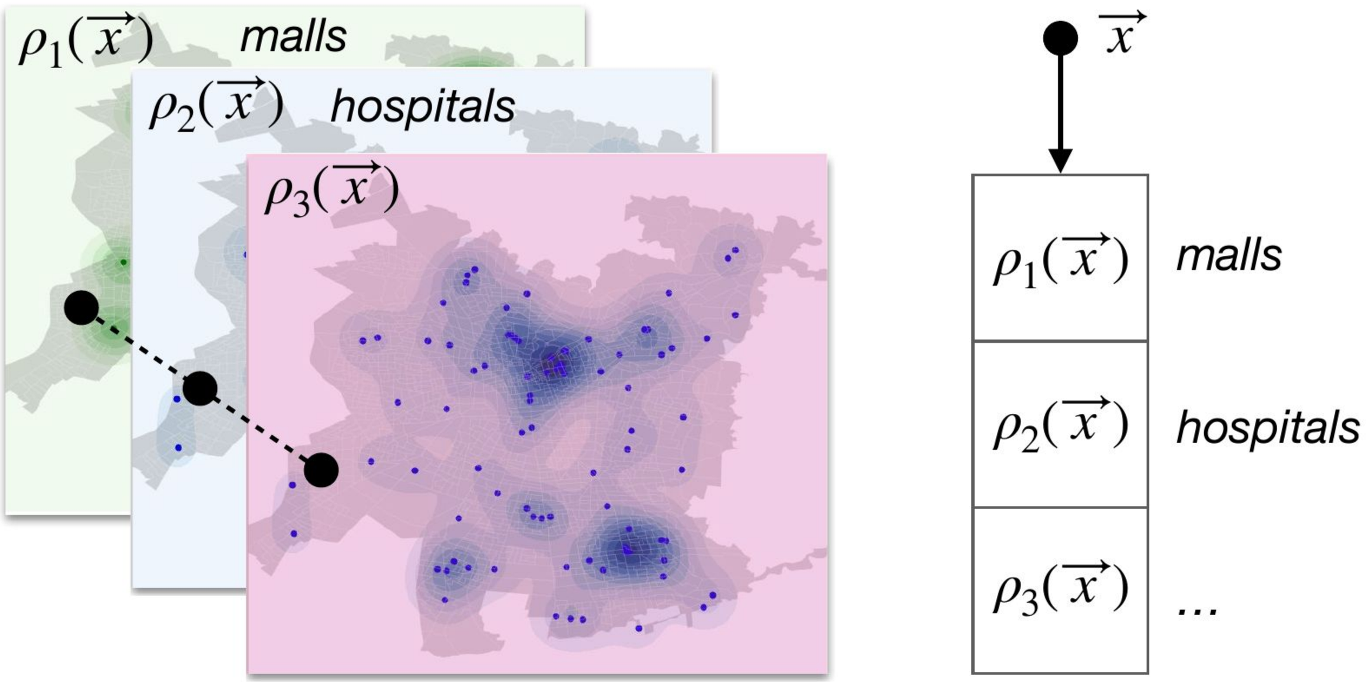
MALLS



HOSPITALS

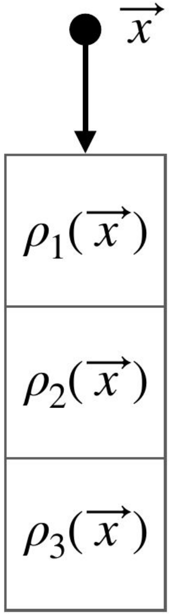
KERNEL DENSITY ESTIMATION TO “SIMULATE THE RANGE OF INFLUENCE” OF THE POIs

POI LAYERS



$\rho_1(\vec{x})$ malls
$\rho_2(\vec{x})$ hospitals
$\rho_3(\vec{x})$
$\vec{x}$
$\rho_1(\vec{x})$ malls
$\rho_2(\vec{x})$ hospitals
$\rho_3(\vec{x})$ ...

GENDER DIFFERENCES IN VISITED LOCATIONS



$L(u)$ = set of locations visited by user u

$$\rho_i^{(u)} = \left\langle \rho_i(\vec{x}) \right\rangle_{\vec{x} \in L(u)}$$

$$\rho_i^F = \left\langle \rho_i^{(u)} \right\rangle_{u \in U_F}$$

$$\rho_i^M = \left\langle \rho_i^{(u)} \right\rangle_{u \in U_M}$$

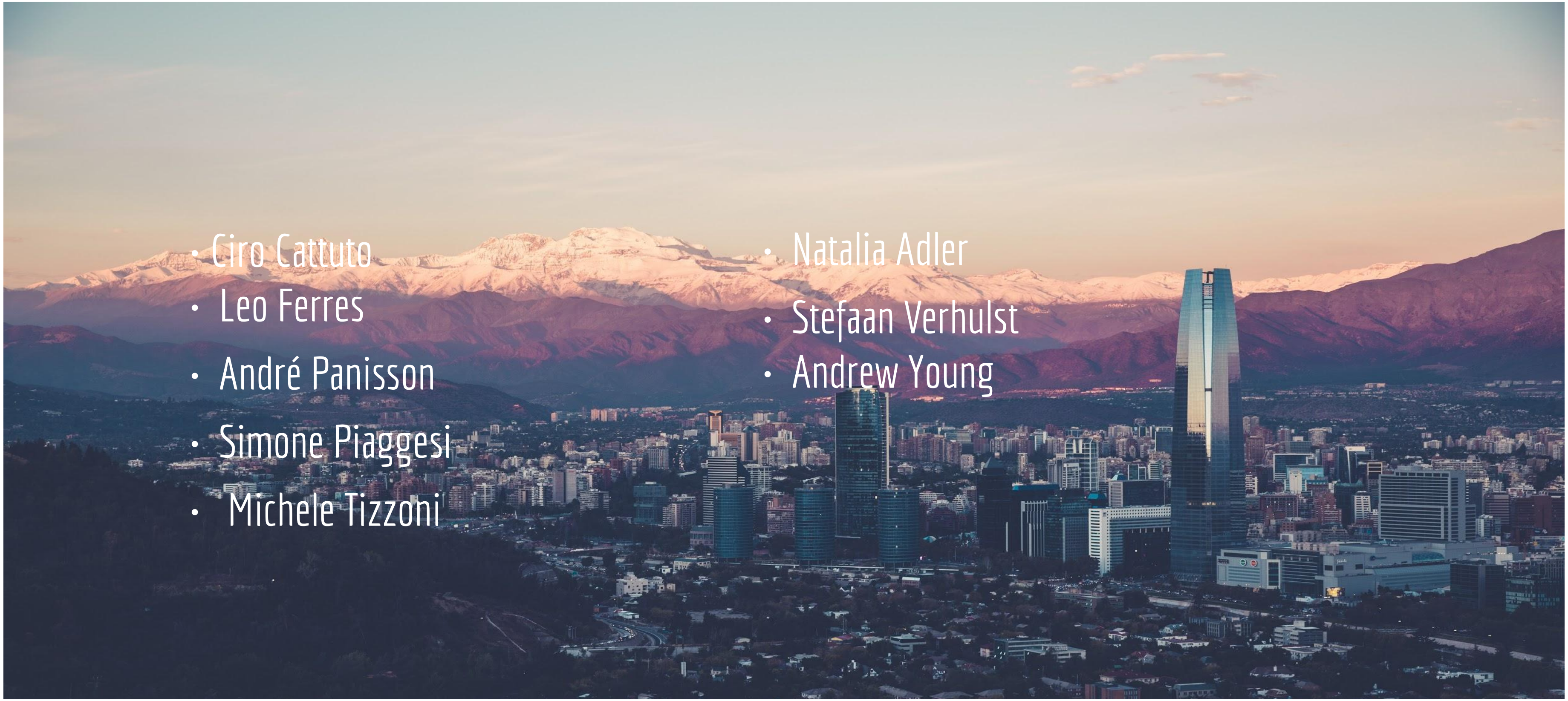
$$r_i = \rho_i^F / \rho_i^M$$

CONCLUSIONS

Gender inequalities in mobility can be captured by mobile phone data.

- Women mobility patterns in Santiago are more localized than men’s.
- The gender gap in mobility widens with lower income and a wider gap in employment
- Access to public transport only mitigates gender differences in mobility
- Some locations more “central” for women: different mobility needs?

https://www.nature.com/articles/s41599-020-0500-x
Gauvin, Laetitia, et al. "Gender gaps in urban mobility." *Humanities and Social Sciences Communications* 7.1 (2020): 1-13.



- Ciro Cattuto
- Leo Ferres
- André Panisson
- Simone Piaggesi
- Michele Tizzoni

- Natalia Adler
- Stefaan Verhulst
- Andrew Young

unicef

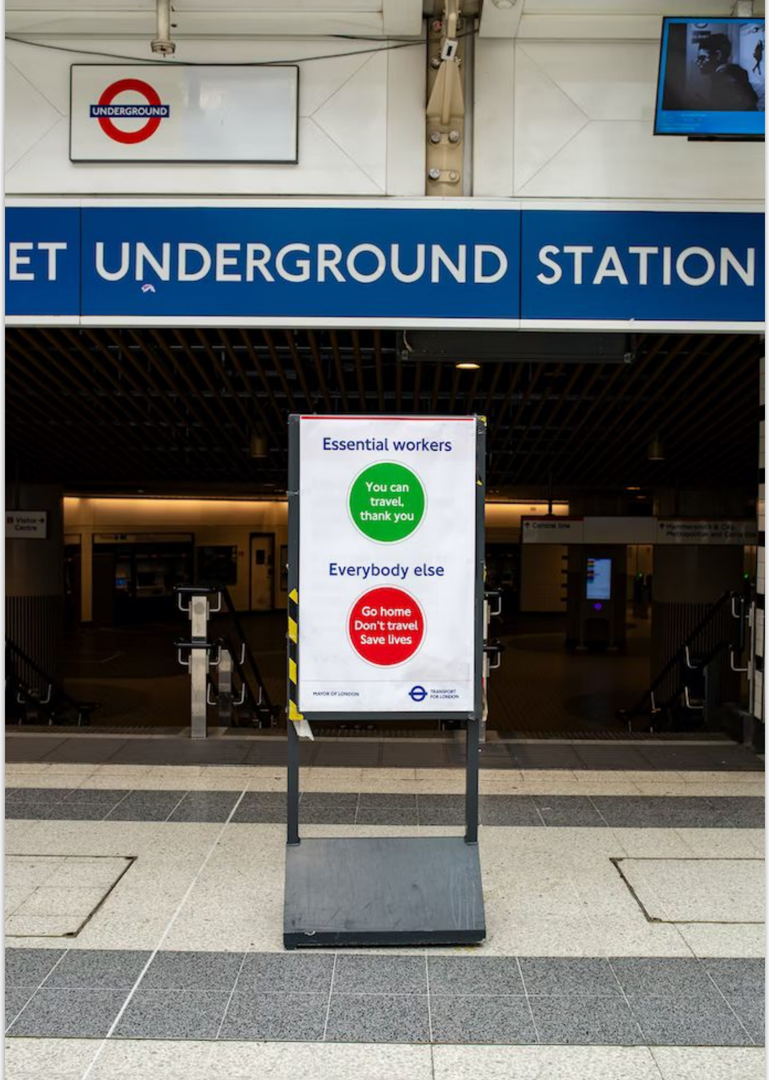
GOVLAB
The Governance Lab @ NYU

INSTITUTE FOR SCIENTIFIC INTERCHANGE FOUNDATION

UDD
Universidad del Desarrollo

Telefonica

DigitalGlobe



COVID-19 & MOBILITY

OBJECTIVES

Measuring in near real-time the impact of COVID-19 non-pharmaceutical intervention (NPIs) in Italy on epidemiologically relevant metrics capturing:

- ❏ long-range mobility
- ❏ short-range mobility
- ❏ spatial proximity

through the analysis of de-identified location data.

COVID-19 Mobility Monitoring project

a research project on human mobility and COVID-19

https://covid19mm.github.io

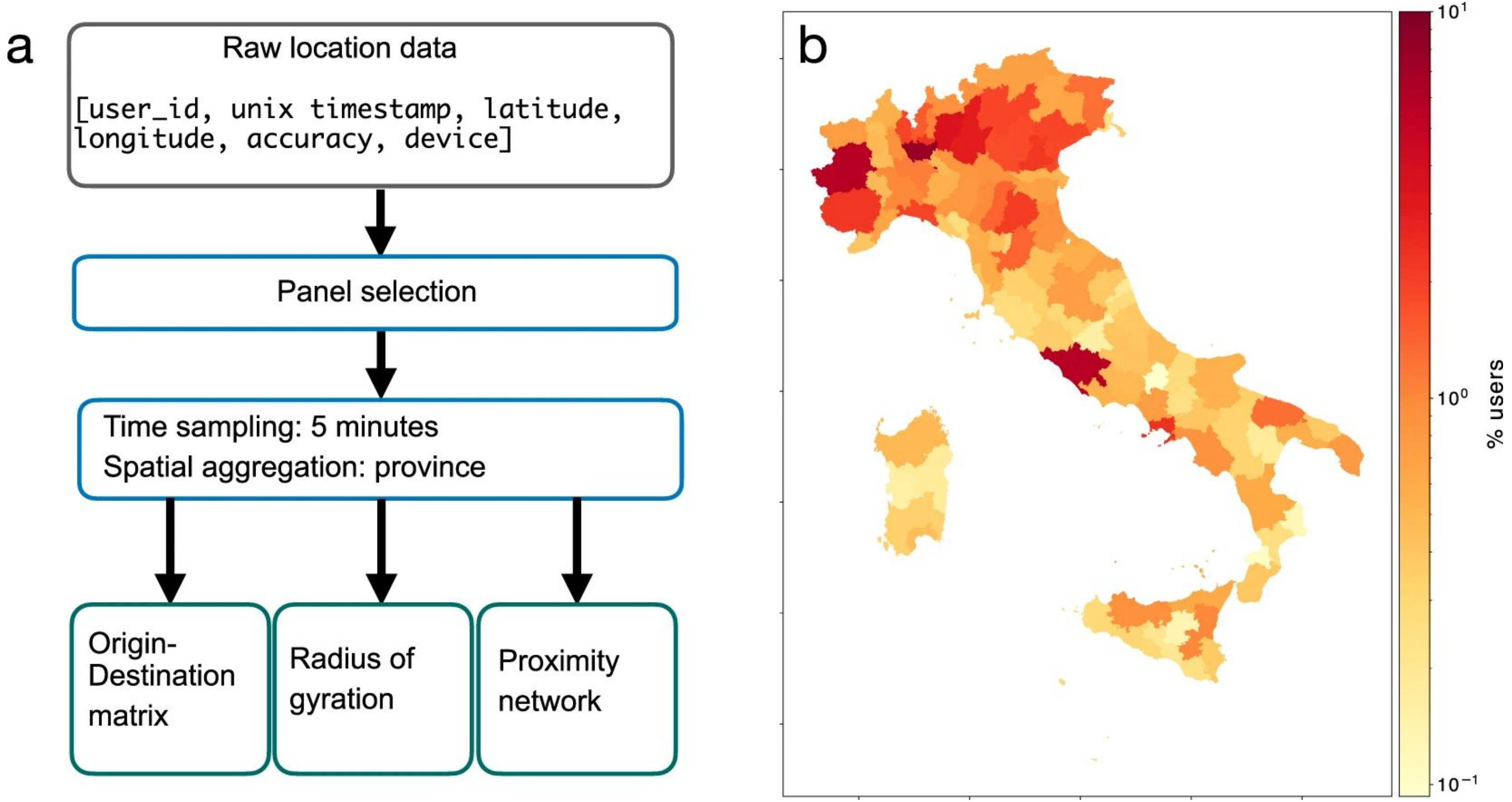
DATASET

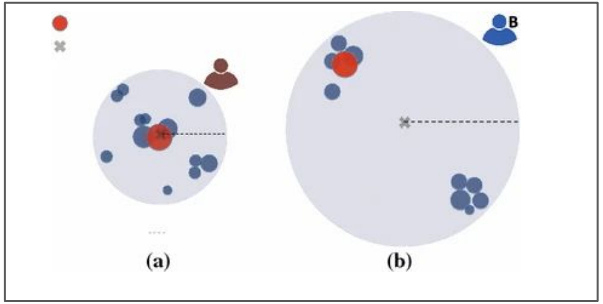
cuebiq

- ~40 000 users
- active every week during the 18 weeks of the study
- 300 millions locations
- Accuracy between 50 and 100 meters

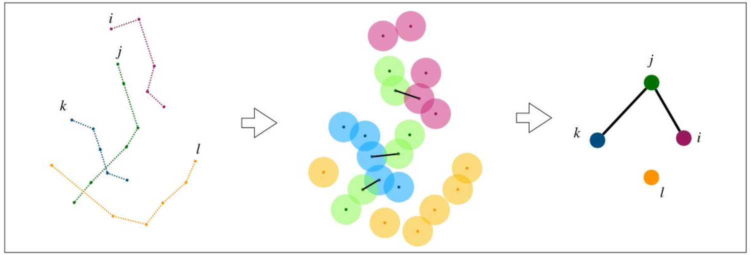
DATA PROTECTION

- anonymized users who have opted-in to provide access to their location data anonymously, through a GDPR-compliant framework
- users can opt-out at any time
- never singled out identifiable individuals / no link to 3rd party
- no demographic information available
- no health information available


a
Raw location data
[user_id, unix timestamp, latitude, longitude, accuracy, device]
Panel selection
Time sampling: 5 minutes
Spatial aggregation: province
Origin-Destination matrix
Radius of gyration
Proximity network
b
10^1
10^0
10^{-1}
% users



Short range mobility : radius of gyration



Spatial proximity : degree (number of neighbours)

Aggregated data is available in the following repo:
https://data.humdata.org/dataset/covid-19-mobility-italy

HOW MOBILITY CHANGES WITH THE DIFFERENT PHASES

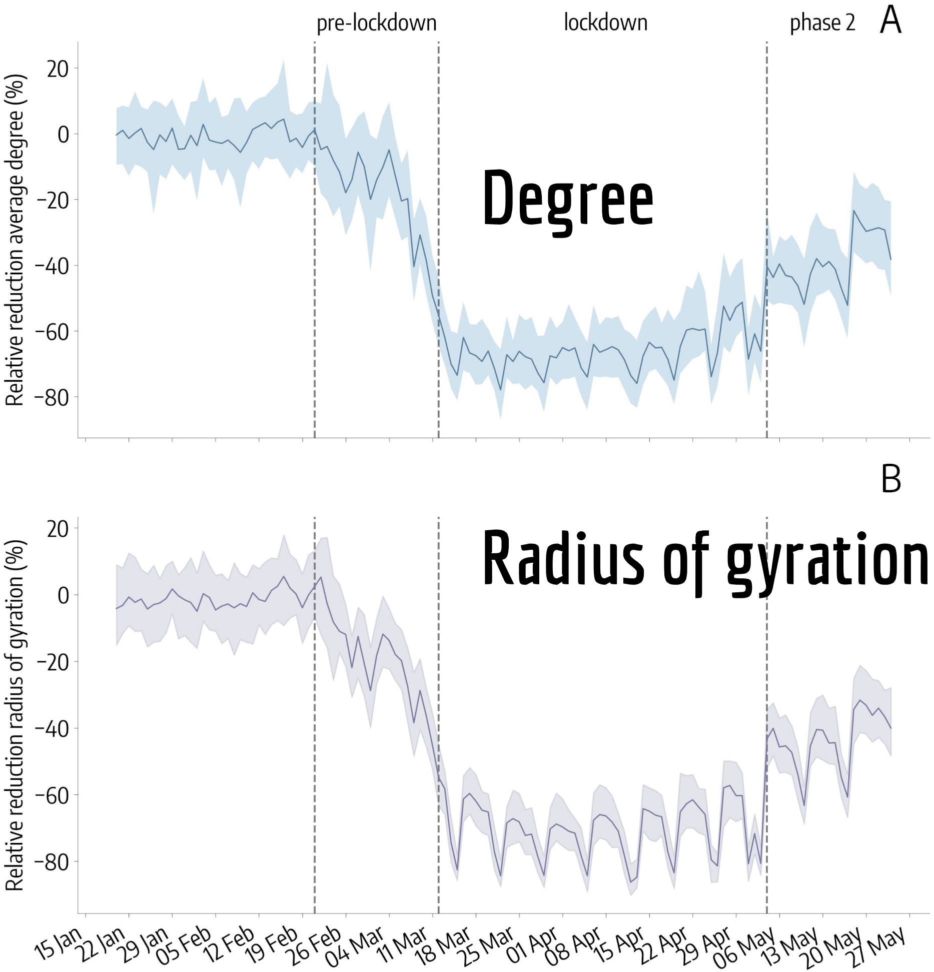
- **Pre-lockdown** (March 2-8): before the enforcement of the national lockdown
- **Lockdown** (March 16-22): strong mobility restrictions
- **Phase 2** starting on May 4th: start of the lift of the restrictions

MOBILITY RESPONSES AT THE NATIONAL LEVEL

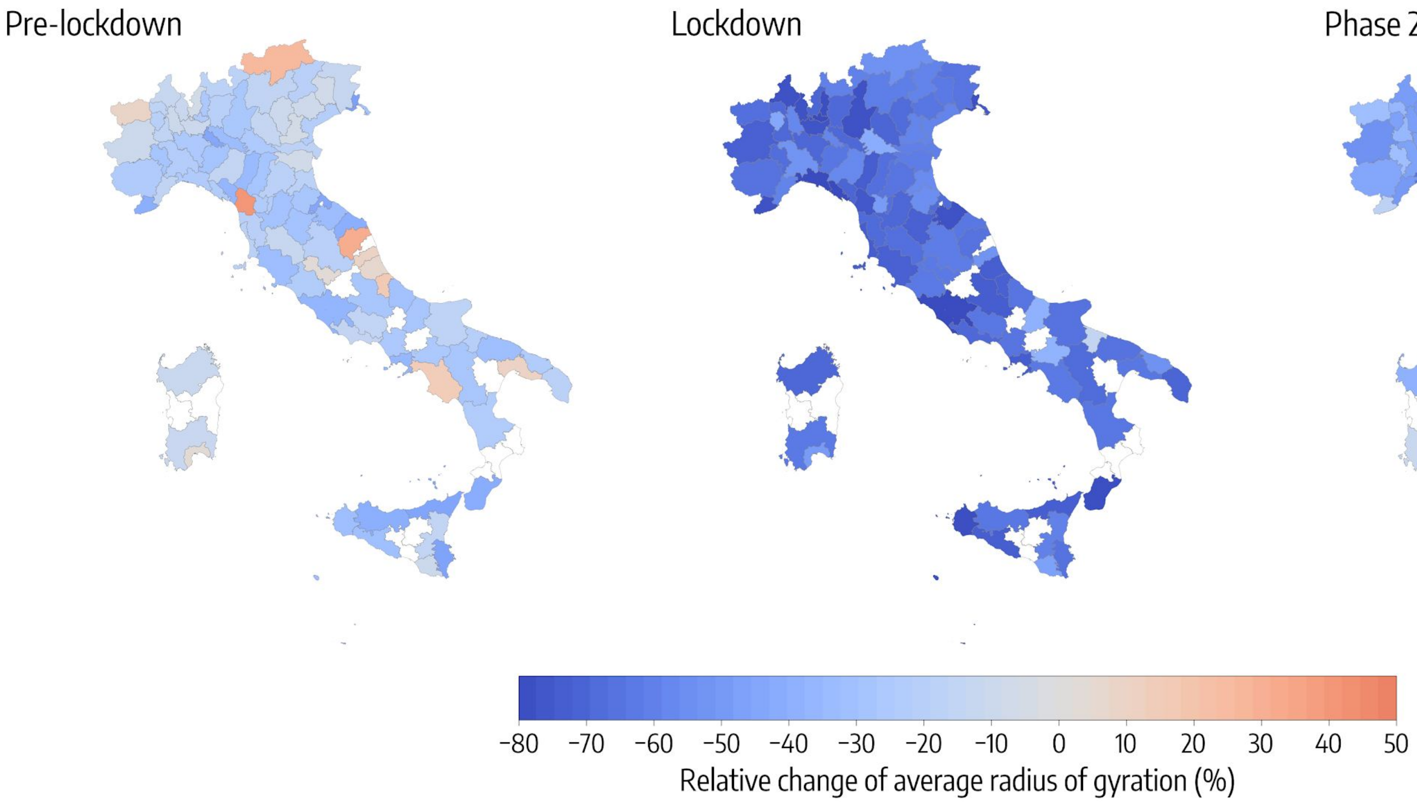
Sharp decline immediately after the first official report of a cluster of COVID-19 cases

Decline mainly due to self-induced behavioral changes

As the lockdown was lifted, the trends started to reverse



SPATIAL VARIATIONS OF RESPONSES TO SOCIAL DISTANCING ORDERS



SOCIOECONOMIC FEATURES

Demographic

- % females
- old-age index (>65 / <15)
- higher education
- population density
- fraction of residential buildings

Economic

- average income
- % unemployment
- % commuters
- % labour force in industry
- % labour force in agriculture
- % labour force in services

Epidemiological

- attack rate (n. of cases)
- closure of bars/restaurants
- large gathering bans
- school closure

Sources: ISTAT, Ministry of Health, Ministry of Finance

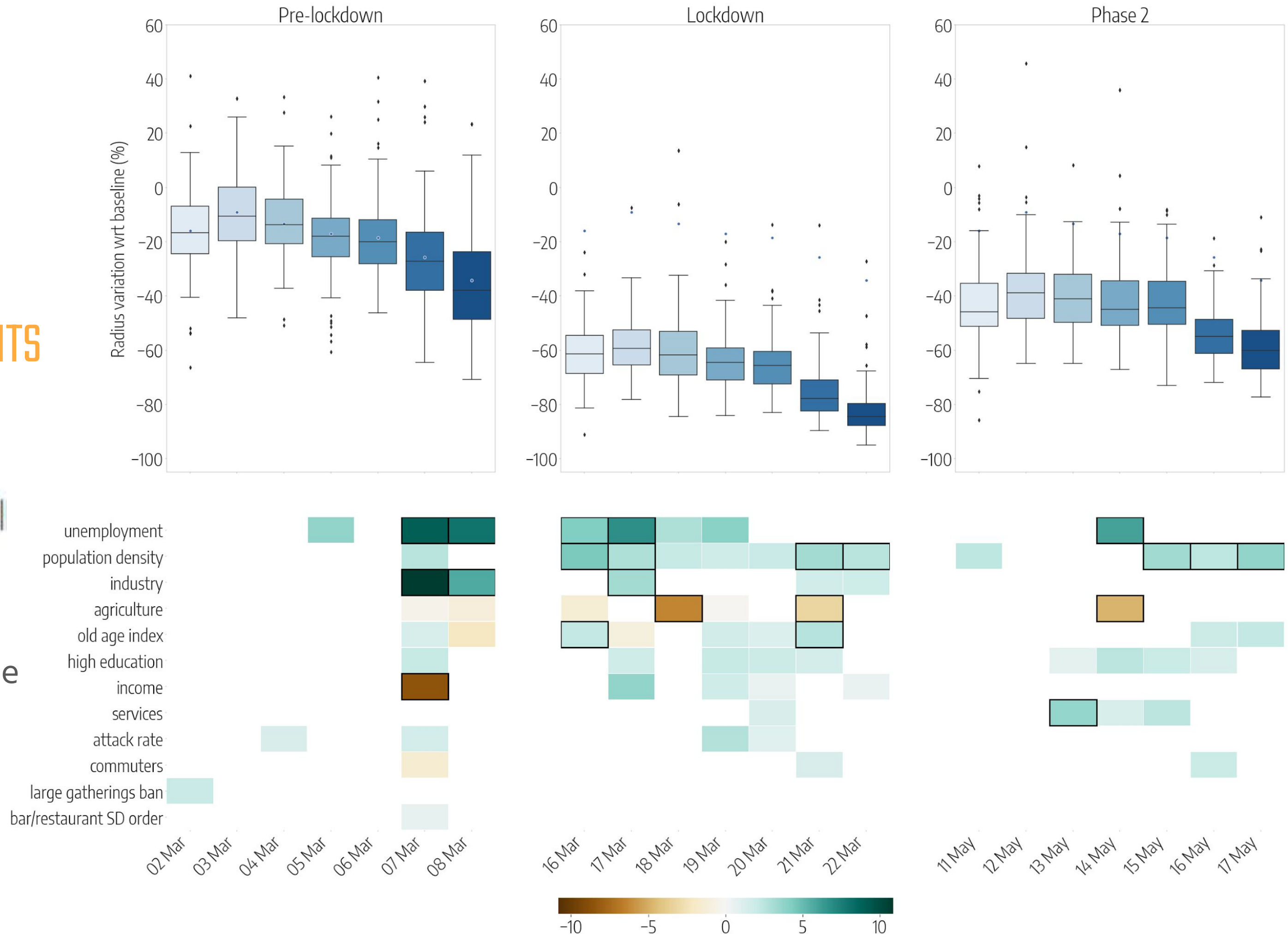
SHORT RANGE MOBILITY
&
SOCIOECONOMIC DETERMINANTS

Lasso regression

$$\frac{1}{2 * n_{\text{samples}}} * \|\mathbf{\Delta x_d} - S\beta\|_2^2 + \alpha * \|\beta|$$

Distribution of workforces explain most of the variations:

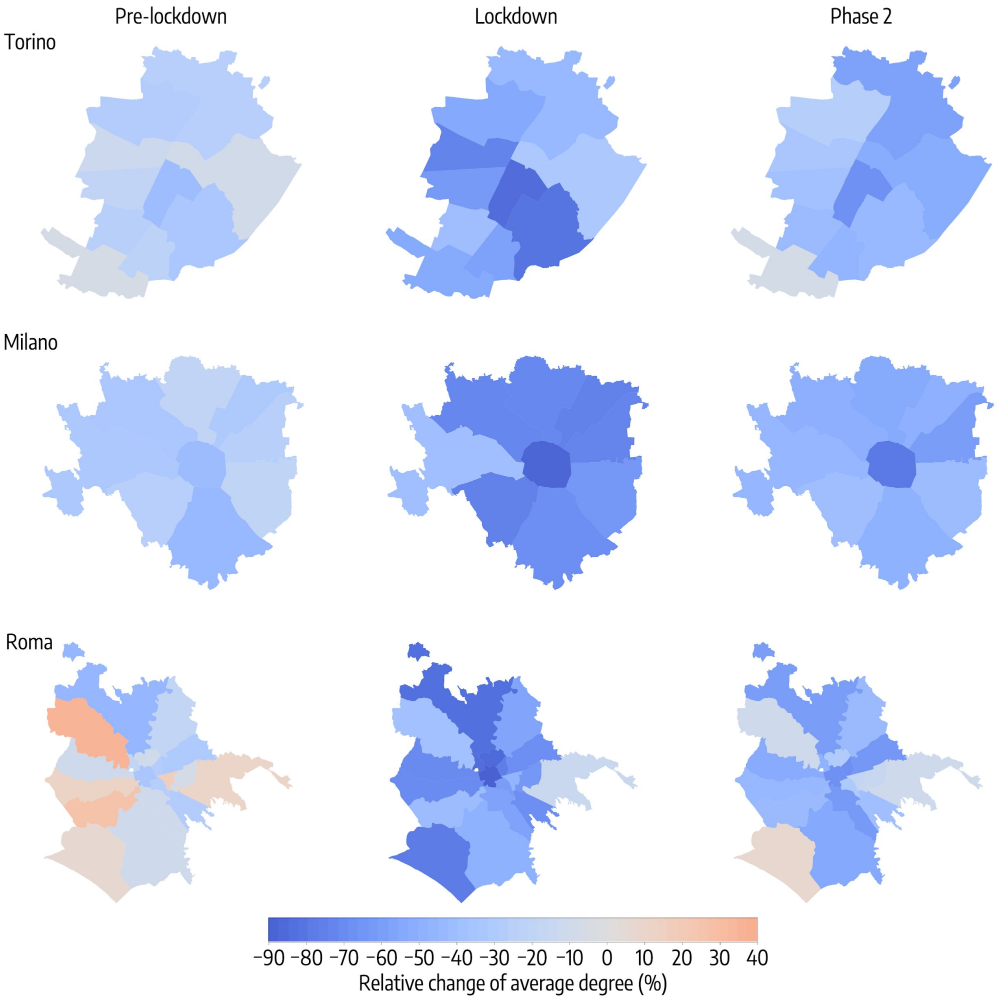
- **Industry**: pre-lockdown & lockdown ↘
-**Services**: phase 2 ↘

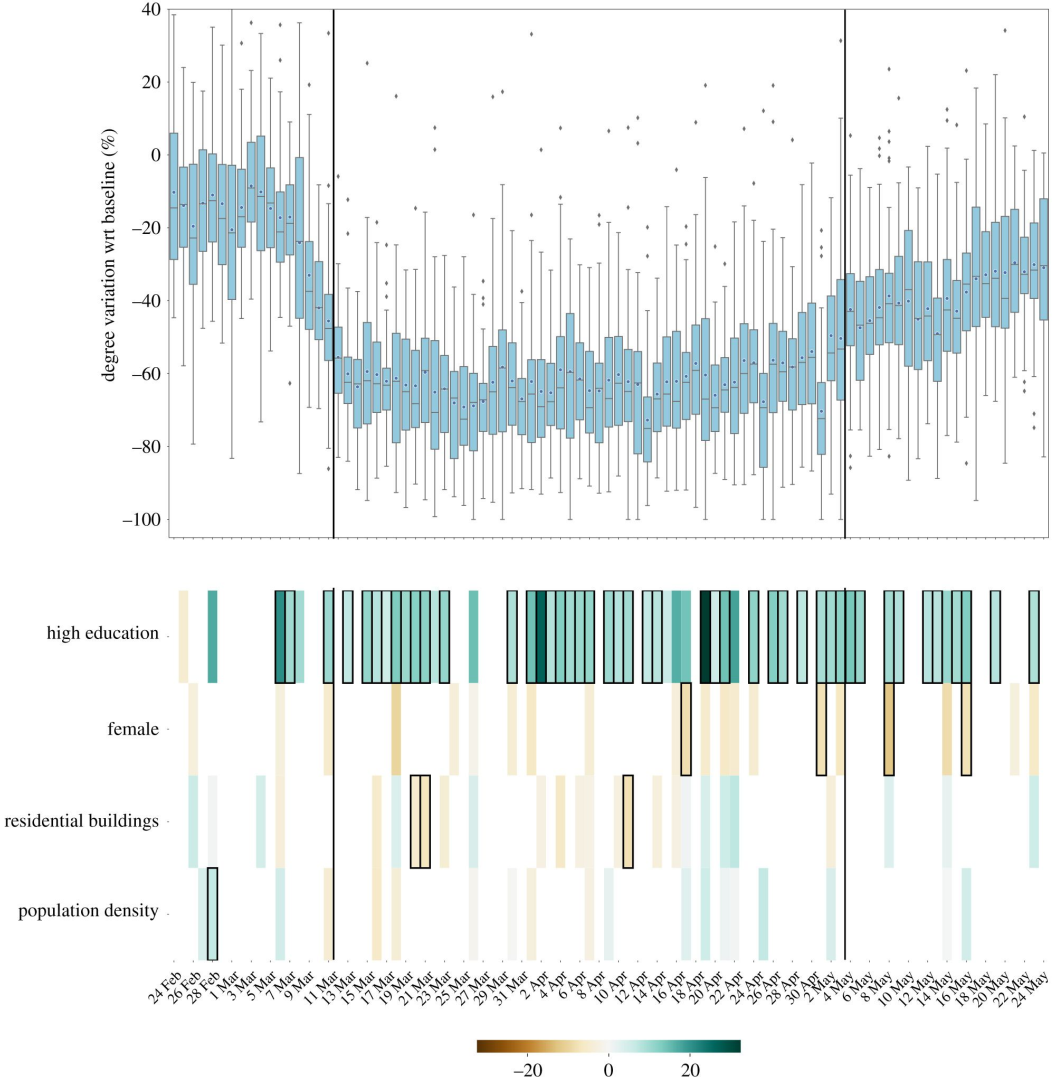


SPATIAL PATTERNS OF VARIATIONS IN CO-LOCATION IN METROPOLITAN AREAS

- Turin and Milan experienced an early decline before the lockdown

- Stronger reduction in the most central districts





A **higher proportion of women** appears to be **negatively associated with the reduction**

Higher education positively associated to reduction

CONCLUSIONS

- Desertification of city center in large urban areas
- The labour market mainly explain the geographical variations in mobility reduction
- Demographic factors like old age index are positively associated to the reduction

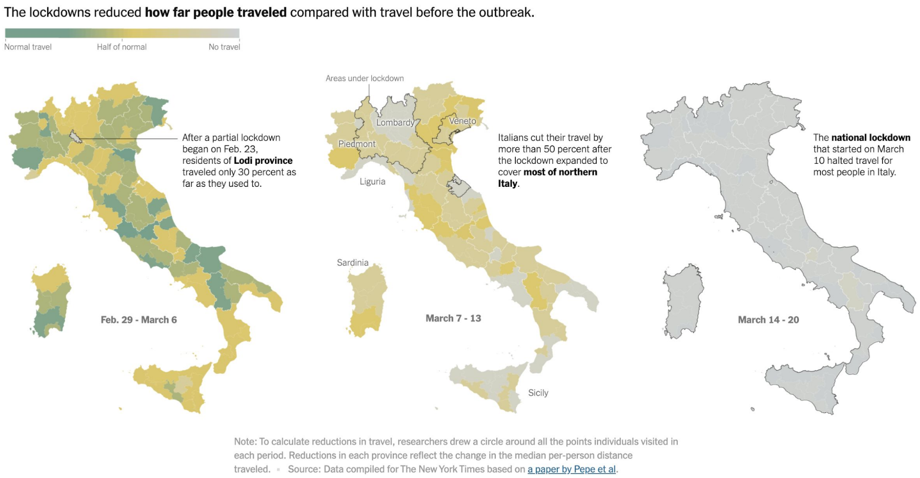
-> unequal impact of mobility restrictions in urban areas

-> Important role of socioeconomic factors of the labour structure in shaping behavioral responses during the full course of the pandemic

https://www.nature.com/articles/s41597-020-00575-2
Pepe, Emanuele, et al. "COVID-19 outbreak response, a dataset to assess mobility changes in Italy following national lockdown." *Scientific data* 7.1 (2020): 1-7.
https://royalsocietypublishing.org/doi/full/10.1098/rsif.2021.0092
Gauvin, Laetitia, et al. "Socio-economic determinants of mobility responses during the first wave of COVID-19 in Italy: from provinces to neighbourhoods." *Journal of The Royal Society Interface* 18.181 (2021): 20210092.

DATA AVAILABILITY

Aggregated data is available at the following repo:
https://data.humdata.org/dataset/covid-19-mobility-italy



https://www.nytimes.com/interactive/2020/04/05/world/europe/italy-coronavirus-lockdown-reopen.html

Emanuele Pepe

Paolo Bajardi

Ciro Cattuto

Michele Tizzoni

Brennan Lake

Filippo Privitera

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PANDEMIC FATIGUE

Temporal variations in adherence to protective behaviors against COVID-19 during the first pandemic wave as a possible consequence of pandemic fatigue

According to the WHO, pandemic fatigue is the demotivation to follow recommended protective behaviours, emerging gradually over time and affected by a number of emotions, experiences and perceptions

increase in mobility under the same restriction level

~

proxy for pandemic fatigue

PANDEMIC FATIGUE

Debate about **the existence and quantifiability of such phenomenon** harshly criticized when it was invoked as an argument against mitigation policies in the UK

However, previous studies have shown that **individual willingness to comply with protective behaviors changed over time**

Social distancing **measures calibrated according to local risk factors**

From a policy perspective, it is important to **assess whether effects of pandemic fatigue are also observed and measurable** when a tiered restriction system is in place

TIERED RESTRICTIONS

Since the beginning of November 2020 until March 2022

10 PM - 5 AM curfew

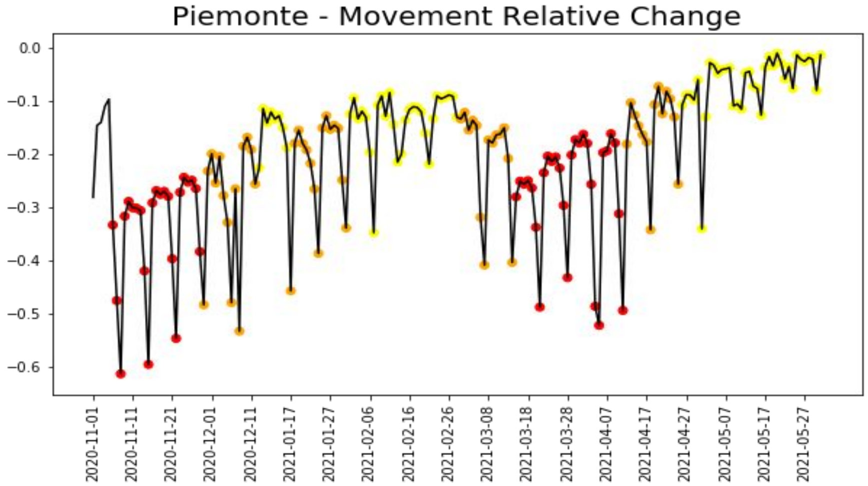
Stay-at-home mandate between 10pm and 5am (restaurants closed)

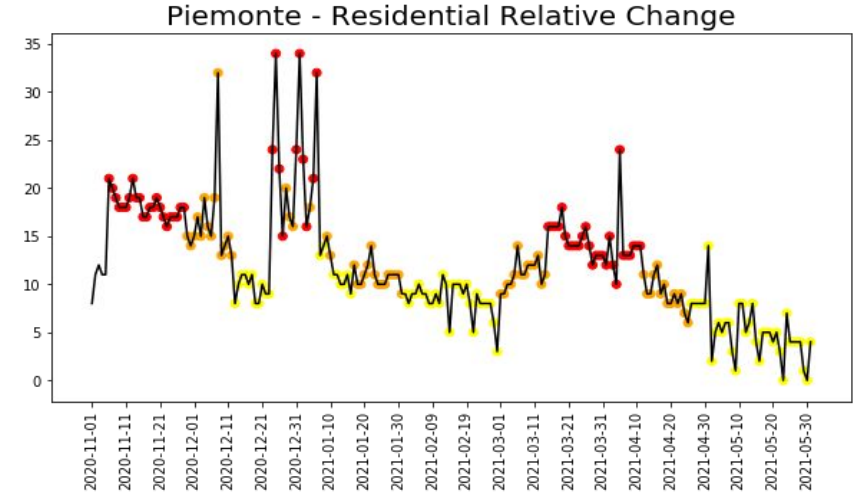
General stay-at-home mandate in the red tier (all shops closed)

- Movement relative change

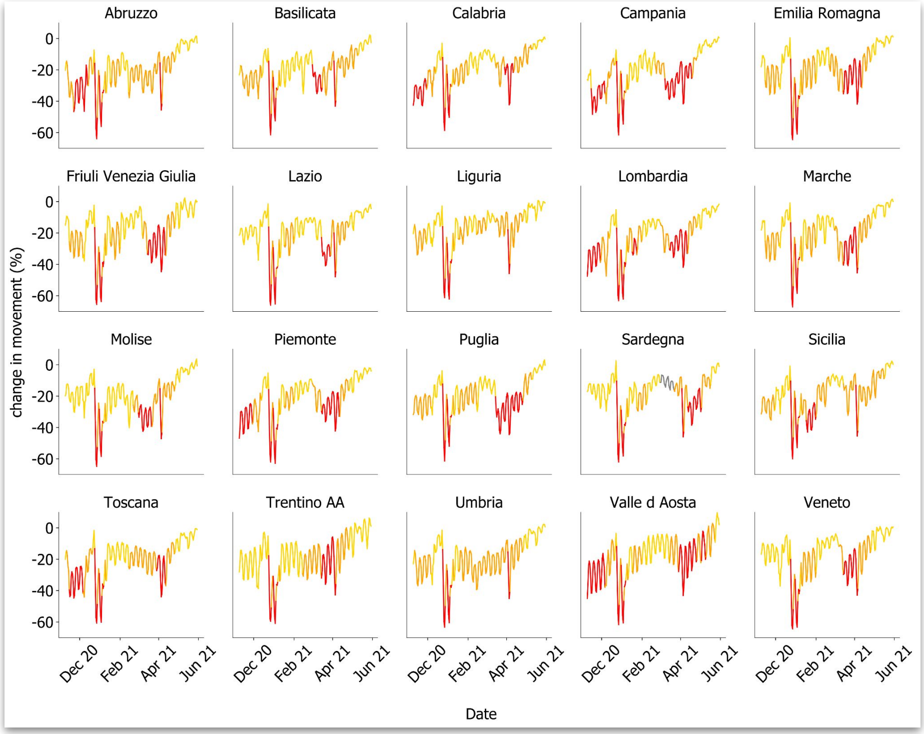
HDX
Humanitarian
Data Exchange

- Residential relative change in time spent at home





https://data.humdata.org/dataset/movement-range-maps
https://www.google.com/covid19/mobility/



Study period: November 2020 -June 2021

How adherence to mobility restrictions changed in time under a tiered system, over this study period?

MIXED EFFECT MODEL

TIme since last change of tier

$$m_{r,t} = \beta_{0,r}(color) + \beta_1 * time + \beta_2 \; (color) * \Delta t + \beta_3 * e(r,t)$$

Global time coefficient

Local time coefficient

Epidemiological Variables [control]

$$\beta_{0,r} = \gamma_{0,0} + \gamma_{0,1}(color) + \gamma_{0,2}(region)$$

$$\beta_1 = \gamma_{1,0}$$

$$\beta_2 = \gamma_{2,0} + \gamma_{2,1}(color)$$

$$\beta_3 = \gamma_{3,0}$$

1. Global time trend
2. Local time trend, independent on the tier
3. Local time trend, dependent of the tier
4. Global time trend + local time trend dependent on the tier

Change in movement

	Dependent variable: Change in movement (%)			
	(1)	(2)	(3)	(4)
Global time trend				
$\gamma_{1,0}$	0.082***			0.082***
	(0.003)			(0.003)
Local time trend				
$\gamma_{2,0}$		0.116***	0.255***	0.155***
		(0.017)	(0.050)	(0.045)
$\gamma_{2,1}$ (orange)			−0.183***	−0.149***
			(0.058)	(0.052)
$\gamma_{2,1}$ (yellow)			−0.135**	−0.165***
			(0.057)	(0.051)
Intercept				
$\gamma_{0,0}$	−39.339***	−32.202***	−33.626***	−41.047***
	(0.862)	(0.936)	(1.073)	(0.993)
$\gamma_{0,1}$ (orange)	9.598***	9.695***	11.768***	11.343***
	(0.501)	(0.561)	(0.862)	(0.770)
$\gamma_{0,1}$ (yellow)	18.024***	18.949***	20.487***	19.990***
	(0.489)	(0.547)	(0.890)	(0.794)
Observations	3,222	3,222	3,222	3,222
Adjusted R^2	0.453	0.313	0.315	0.454
AIC	23,638	24,368	24,362	23,632

Note:
*p<0.1;
**p<0.05;
***p<0.01

https://doi.org/10.1371/journal.pdig.0000035.t001

Change in residential time

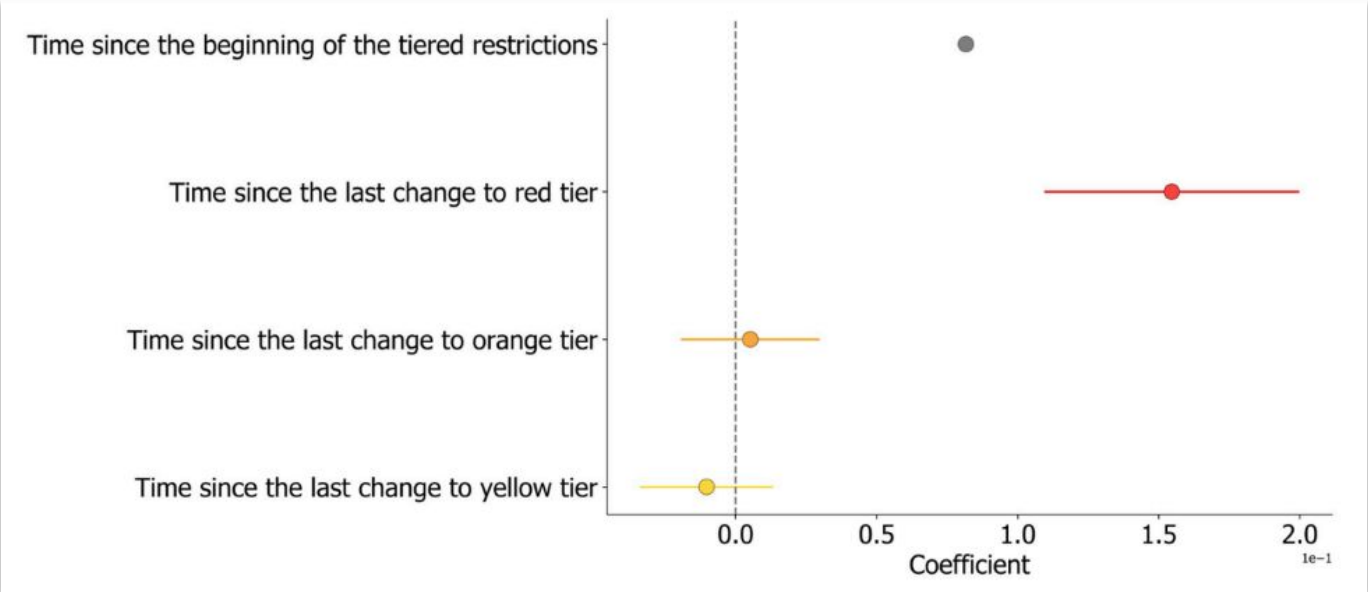
	Dependent variable: Change in residential time (%)			
	(1)	(2)	(3)	(4)
Global time trend				
$\gamma_{1,0}$	−0.040***			−0.039***
	(0.001)			(0.001)
Local time trend				
$\gamma_{2,0}$		−0.057***	−0.092***	−0.045***
		(0.005)	(0.016)	(0.011)
$\gamma_{2,1}$ (orange)			0.066***	0.051***
			(0.018)	(0.013)
$\gamma_{2,1}$ (yellow)			0.017	0.028**
			(0.018)	(0.013)
Intercept				
$\gamma_{0,0}$	18.814***	15.312***	15.592***	19.225***
	(0.218)	(0.293)	(0.335)	(0.250)
$\gamma_{0,1}$ (orange)	−4.056***	−4.087***	−4.810***	−4.628***
	(0.125)	(0.173)	(0.267)	(0.193)
$\gamma_{0,1}$ (yellow)	−7.248***	−7.554***	−7.676***	−7.520***
	(0.121)	(0.169)	(0.274)	(0.198)
Observations	3,401	3,401	3,401	3,401
Adjusted R^2	0.705	0.433	0.436	0.707
AIC	15,645	17,873	17,853	15,626

Note:
*p<0.1;
**p<0.05;
***p<0.01

https://doi.org/10.1371/journal.pdig.0000035.t002

Global decrease in adherence over time

Model estimates - relative change in movement



Global time trend : 0.08% daily increase in relative change of movements
Local time trend : 0.16% daily additional increase in relative mobility (red tier)

To better contextualize our results, the estimated general time trend corresponds to more than **15% increase in the relative mobility change over the whole study period**

2 weeks under a **yellow tier** : average **increase** in movements of about **1%**

2 weeks under the **red tier** : average **3% increase** in the relative **mobility**

TAKE-HOME MESSAGE

Adherence can be difficult to sustain over time

Stronger effect with more stringent restrictions

need to consider interplay between the efficacy of restrictions and their sustainability over time

PLOS DIGITAL HEALTH

RESEARCH ARTICLE

Evidence of pandemic fatigue associated with stricter tiered COVID-19 restrictions

Federico Delussu, Michele Tizzoni, Laetitia Gauvin*

ISI Foundation, via Chisola 5, 10126, Turin, Italy

These authors contributed equally to this work.
* laetitia.gauvin@isi.it

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Delussu, F., Tizzoni, M., & Gauvin, L. (2022). **Evidence of pandemic fatigue associated with stricter tiered COVID-19 restrictions**. *PLOS Digital Health*, *1*(5), e0000035.
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Pepe, E., Bajardi, P., Gauvin, L., Privitera, F., Lake, B., Cattuto, C., & Tizzoni, M. (2020). **COVID-19 outbreak response, a dataset to assess mobility changes in Italy following national lockdown.** *Scientific data*, *7*(1), 230.
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Mazzoli, M., Pepe, E., Mateo, D., Cattuto, C., Gauvin, L., Bajardi, P., *et al* (2021). **Interplay between mobility, multi-seeding and lockdowns shapes COVID-19 local impact.** *PLoS computational biology*, *17*(10), e1009326.
Woskie, L. R., Hennessy, J., Espinosa, V., Tsai, T. C., Vispute, S., Jacobson, B. H., *et al (*2021). **Early social distancing policies in Europe, changes in mobility & COVID-19 case trajectories: Insights from Spring 2020.** *PLoS One*, *16*(6), e0253071.

laetitia.gauvin@ird.fr

@laetitiagvn