Intersectional approach of everyday geography

Julie Vallée, Maxime Lenormand

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UrbanSys 2021, Lyon

INTERSECTIONAL APPROACH OF EVERYDAY GEOGRAPHY

Julie Vallée & Maxime Lenormand

Géographie-cités, CNRS, Paris, France

TETIS, INRAE, Montpellier, France

cnrs

Géographie-cités
UMR 8504

TERRITOIRE ENVIRONNEMENT TELEDETECTION
INFORMATION SPATIALE
tetis

INRAE

Motivations

Only few studies about everyday segregation… and they usually explore single axe of difference (ie. social class) with a single-city focus

Measuring segregation using patterns of daily travel behavior: A social interaction based model of exposure

Steven Farber [a,*], Morton O'Kelly [b], Harvey J. Miller [b], Tijs Neutens [c]

Social segregation around the clock in the Paris region (France)

Guillaume Le Roux *, Julie Vallée, Hadrien Commenges

Beyond residential segregation: A spatiotemporal approach to examining multi-contextual segregation

Yoo Min Park*, Mei-Po Kwan

The temporal variation of ethnic segregation in a city: Evidence from a mobile phone use dataset

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From residence to movement: The nature of racial segregation in everyday urban mobility

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Here we explore how local population concentration change throughout the day

- ✓ crossing three axes of differences (gender, age and education) from an intersectional lens
- ✓ in 49 French city regions to make comparisons across and within city regions possible

DATA

- From public transportation surveys in 49 French city regions
  - 385,000 respondents
  - 1.7 millions of trips
- Trips dataset to hourly location dataset
  → displayed in MOBILISCOPE platform
- Present population
  - space (district scale – 2572 French districts)
  - hour (24 hours – a weekday)
  - social group
    - ✓ gender (women; men)
    - ✓ age (4 age groups)
    - ✓ education (4 educational groups)

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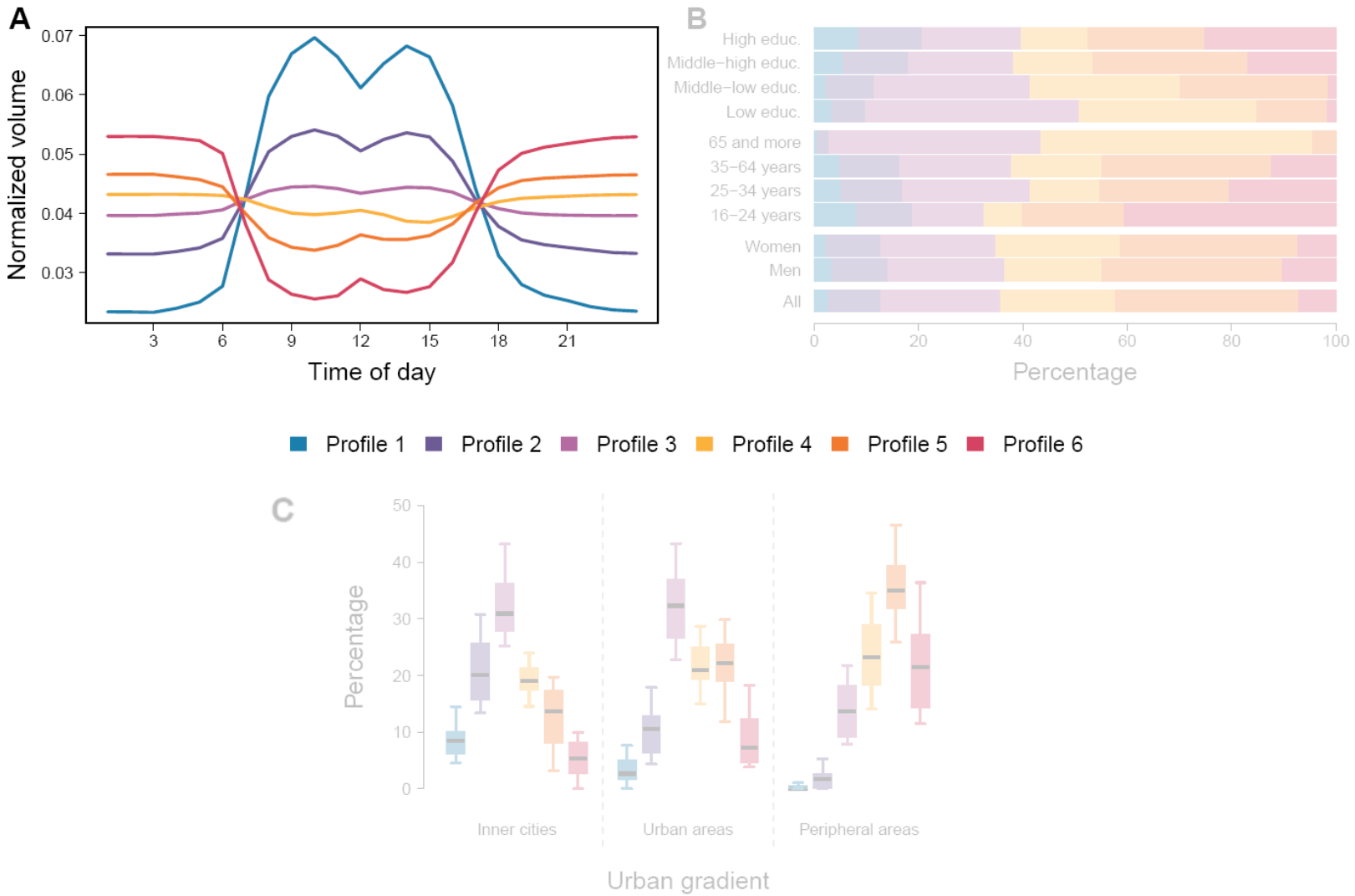
→ 28 281 socio-districts after cleaning

Clustering of hourly profiles



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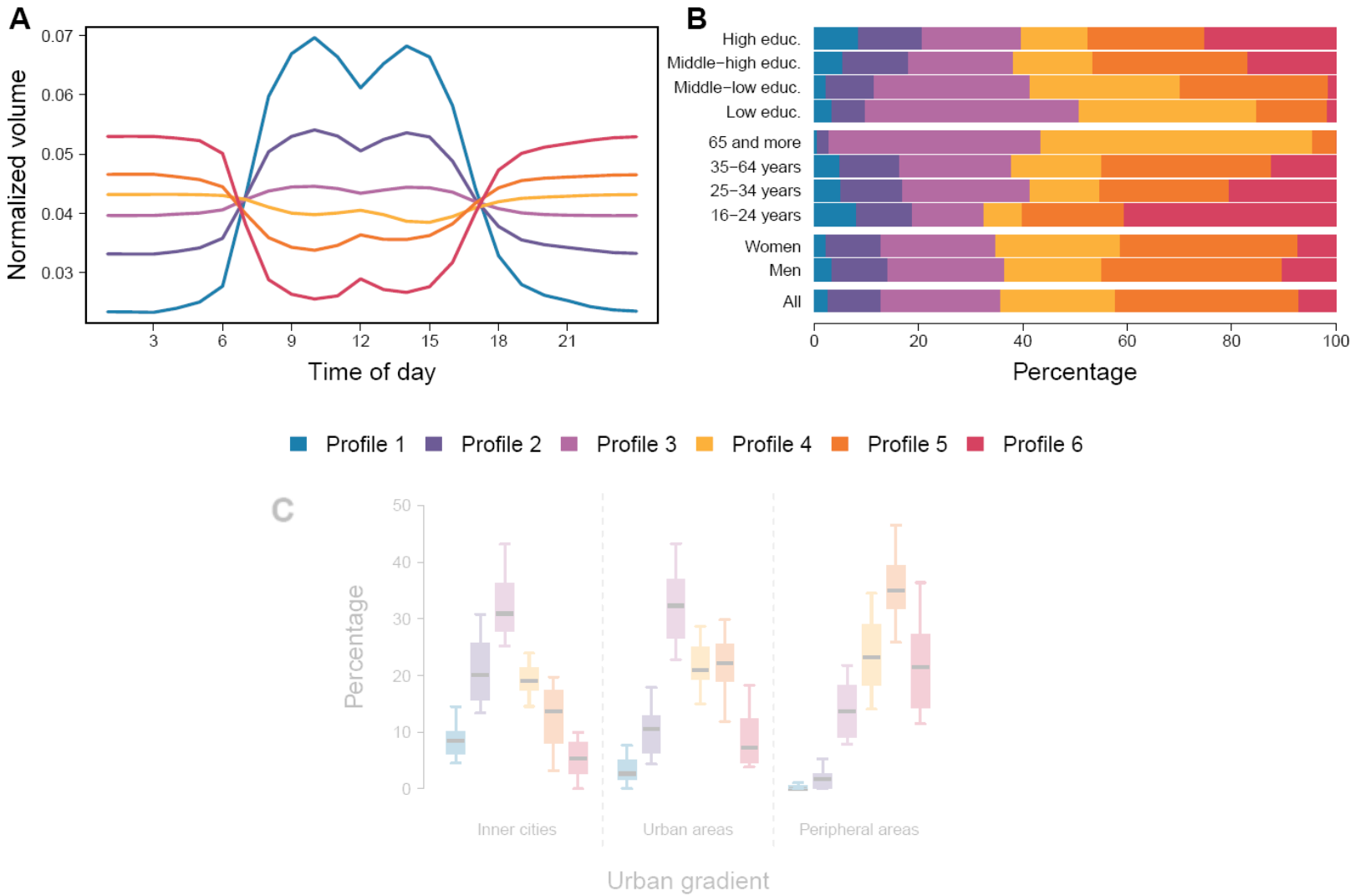

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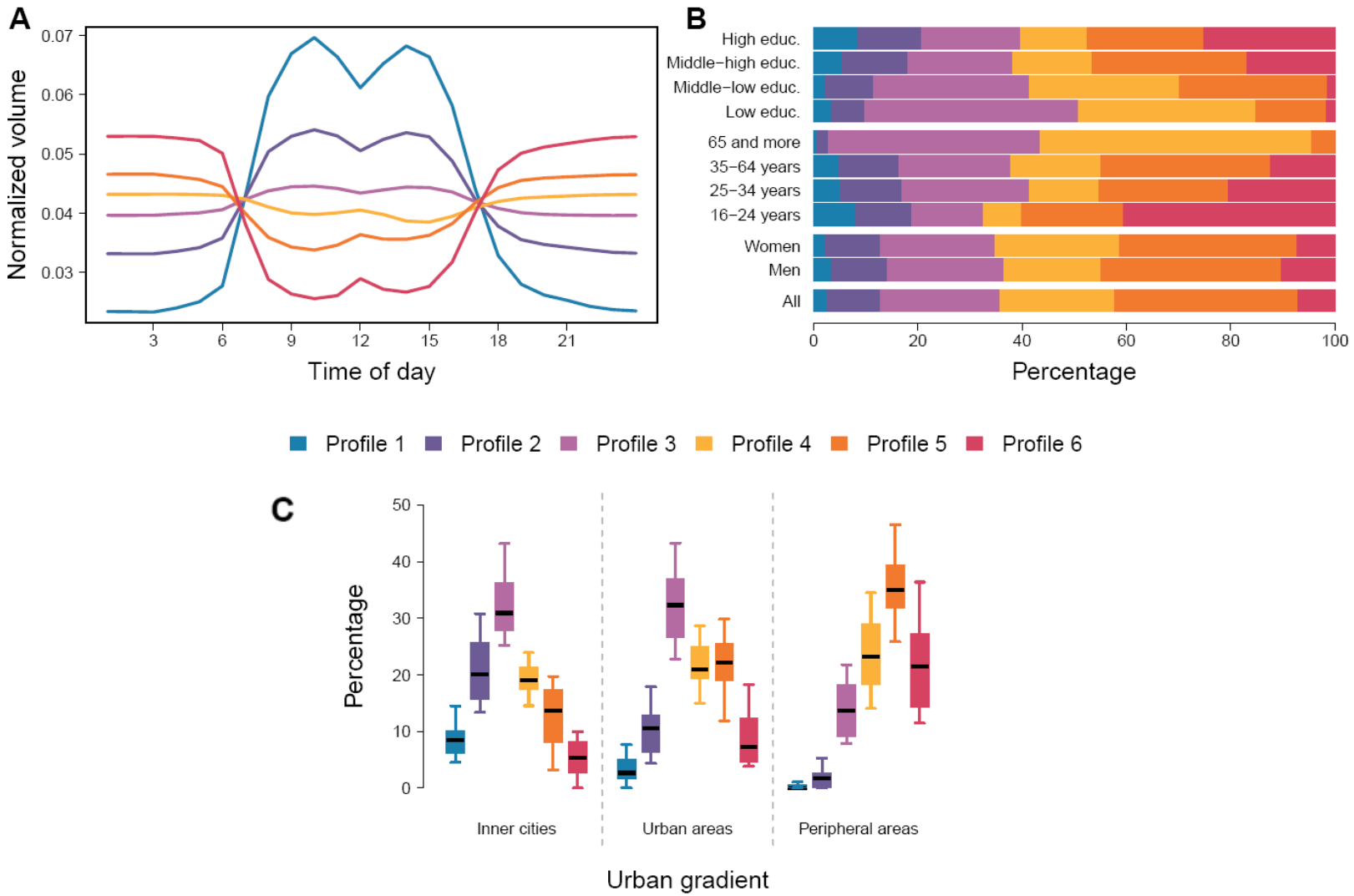
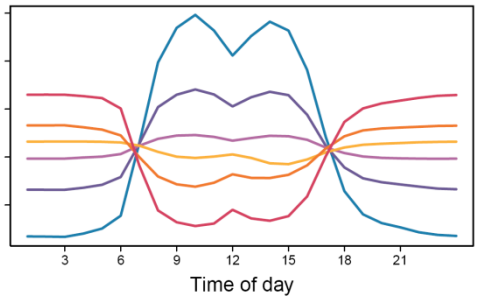
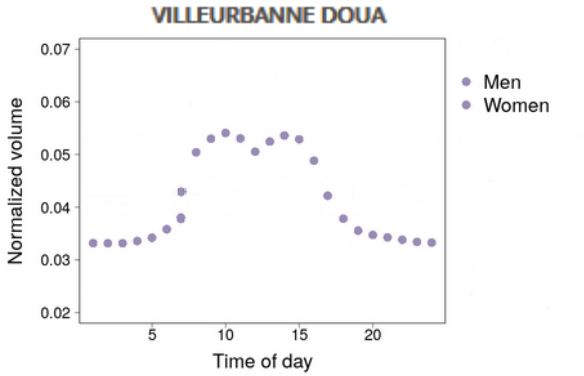
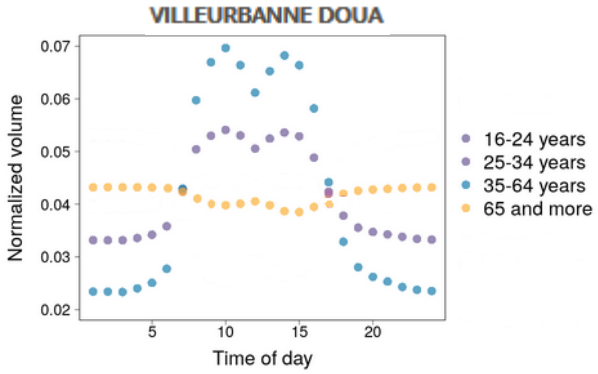


Mismatch in hourly profiles – Methods

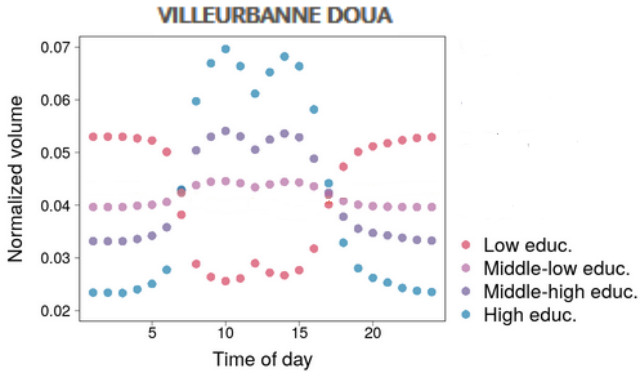




Gender mismatch



Age mismatch



Education mismatch

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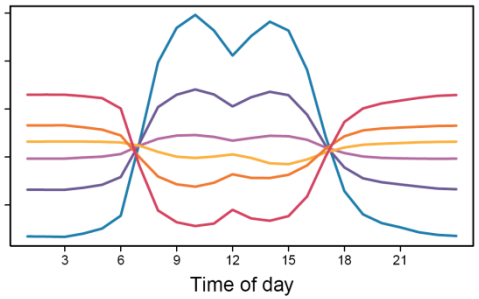

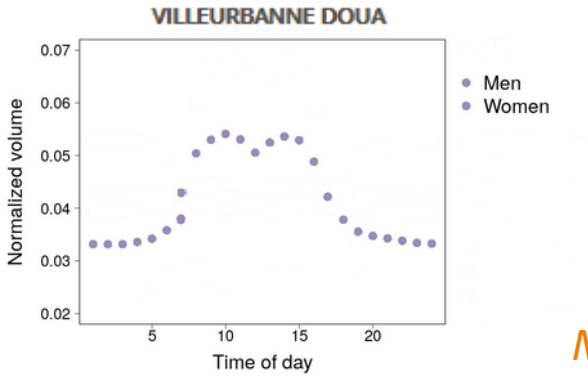

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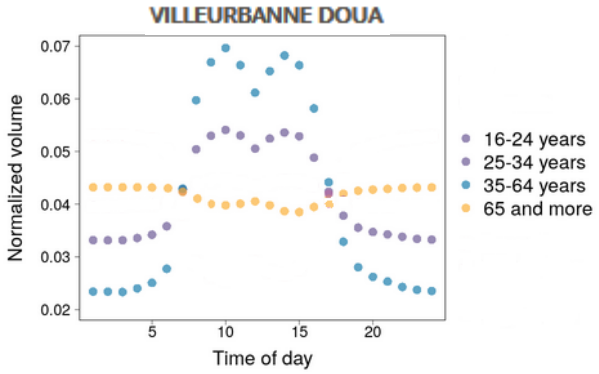
Mismatch men/women = 0



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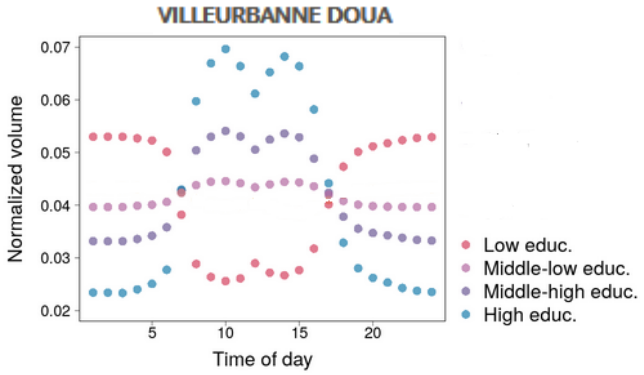

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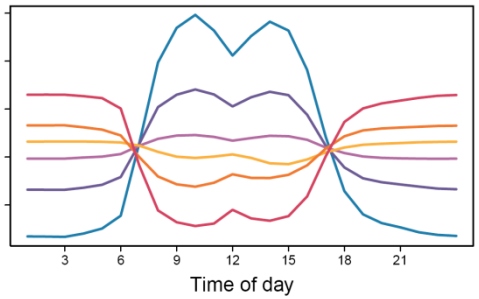

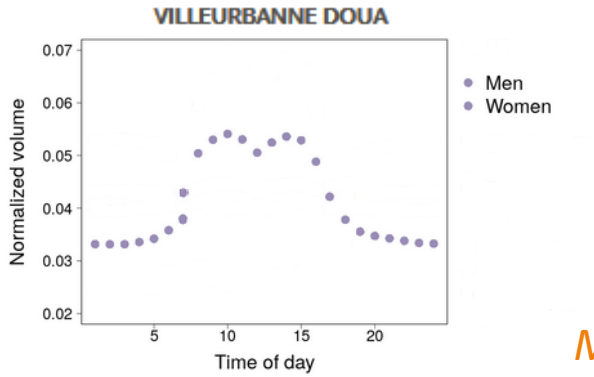

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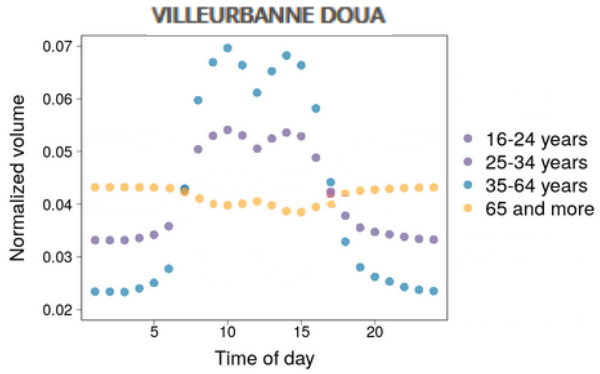
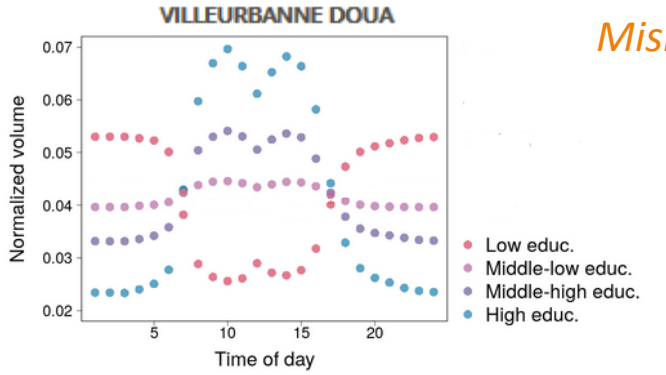


Age mismatch

Mismatch low/high educ. = 1



Education mismatch

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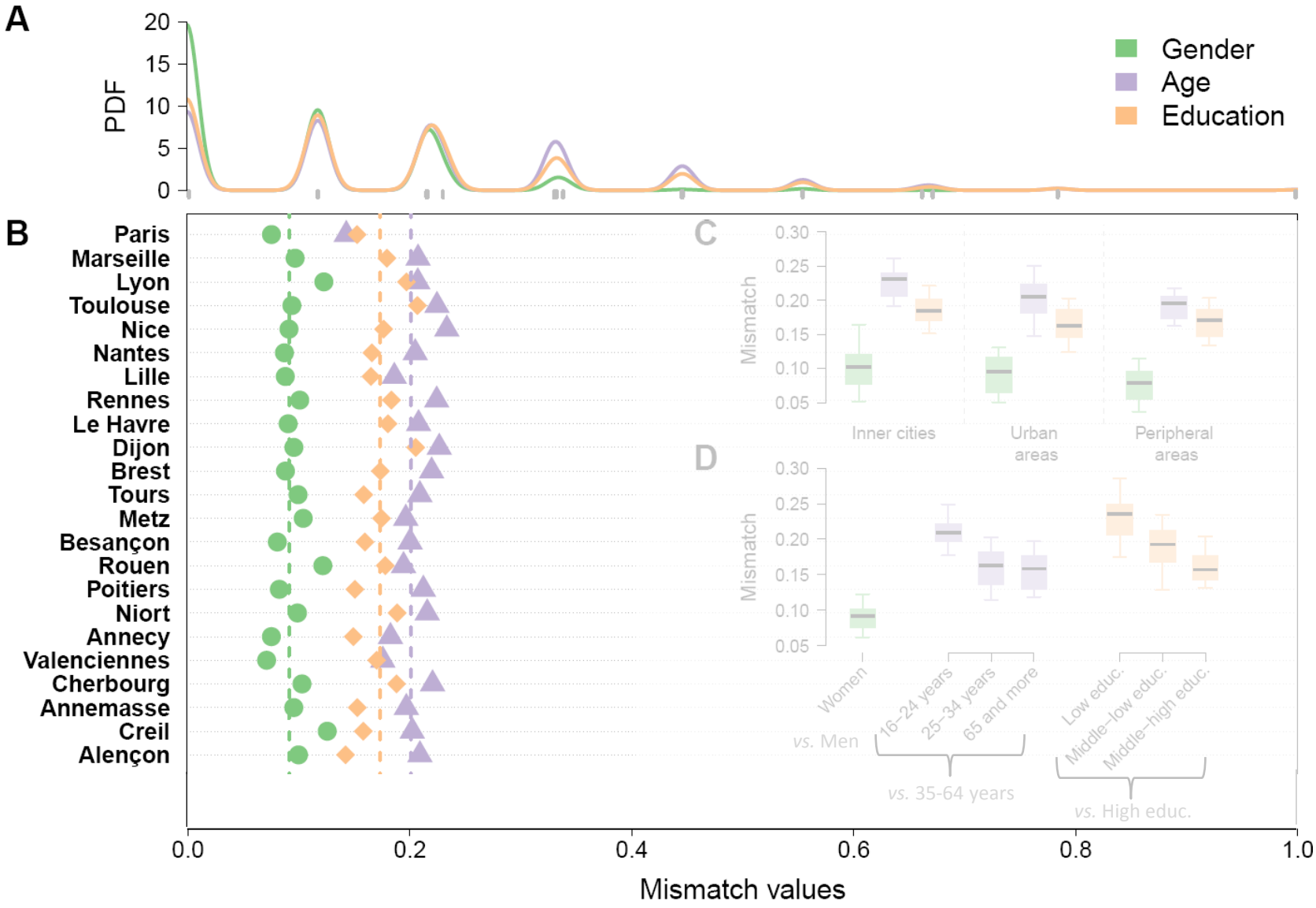

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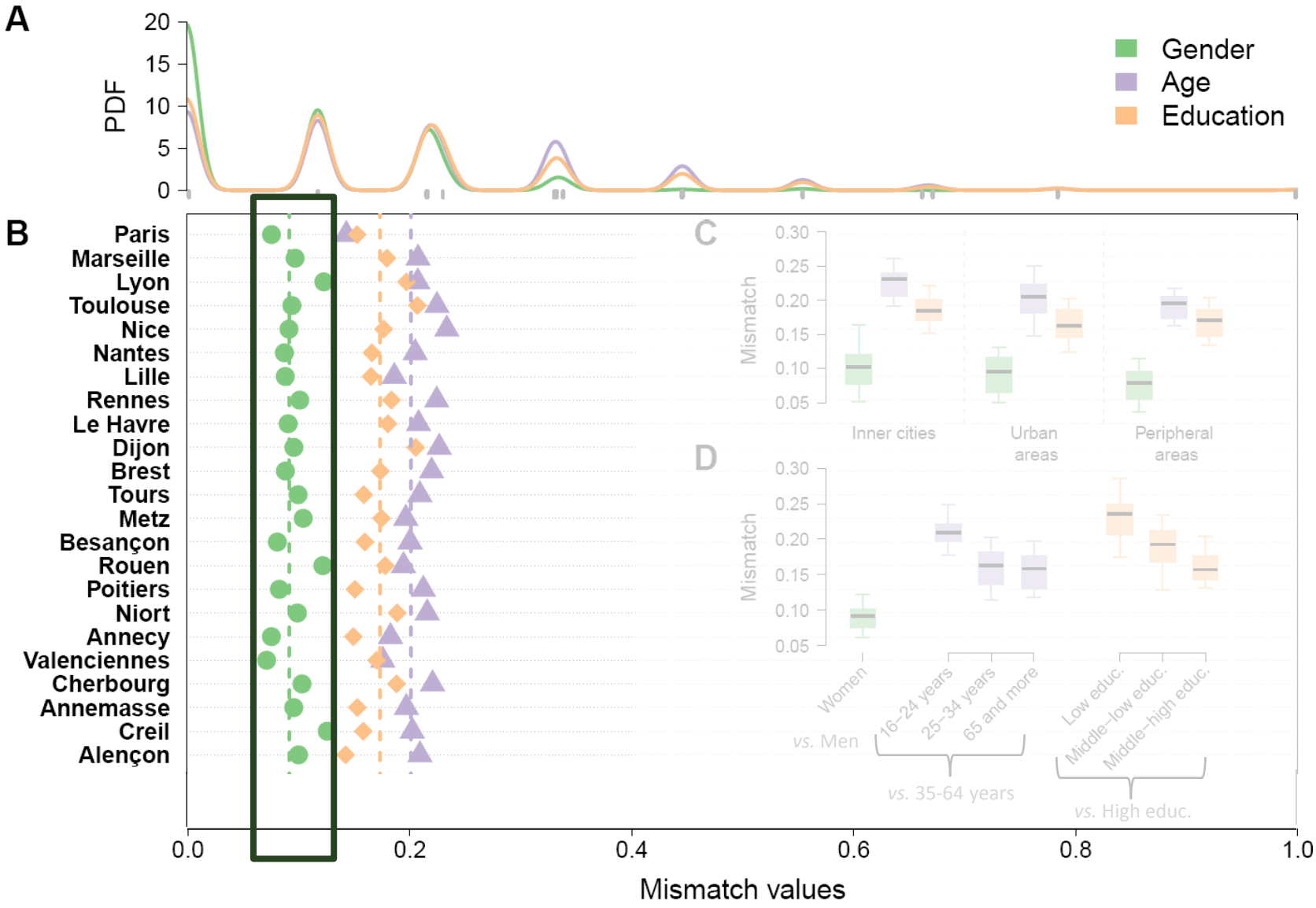

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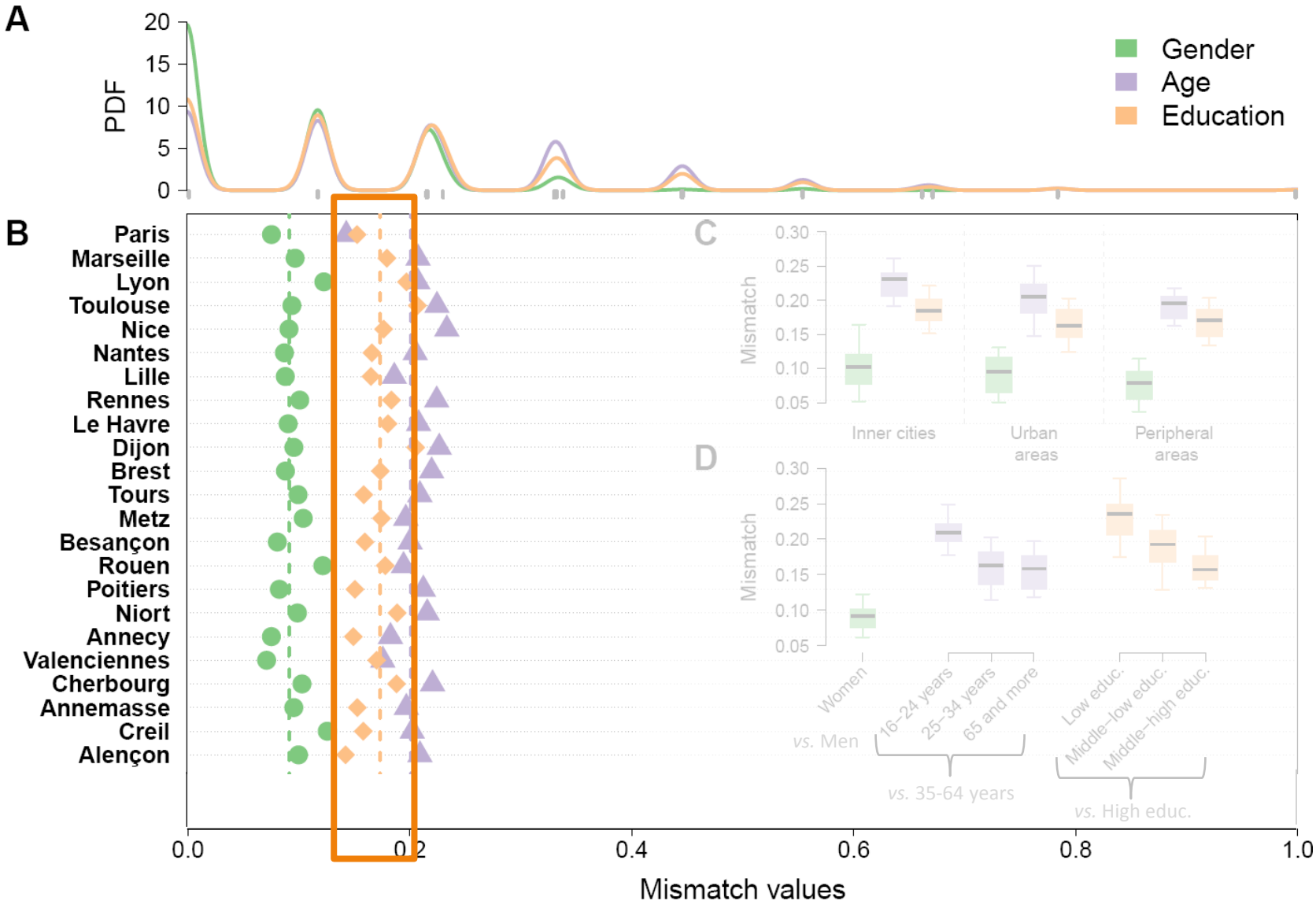

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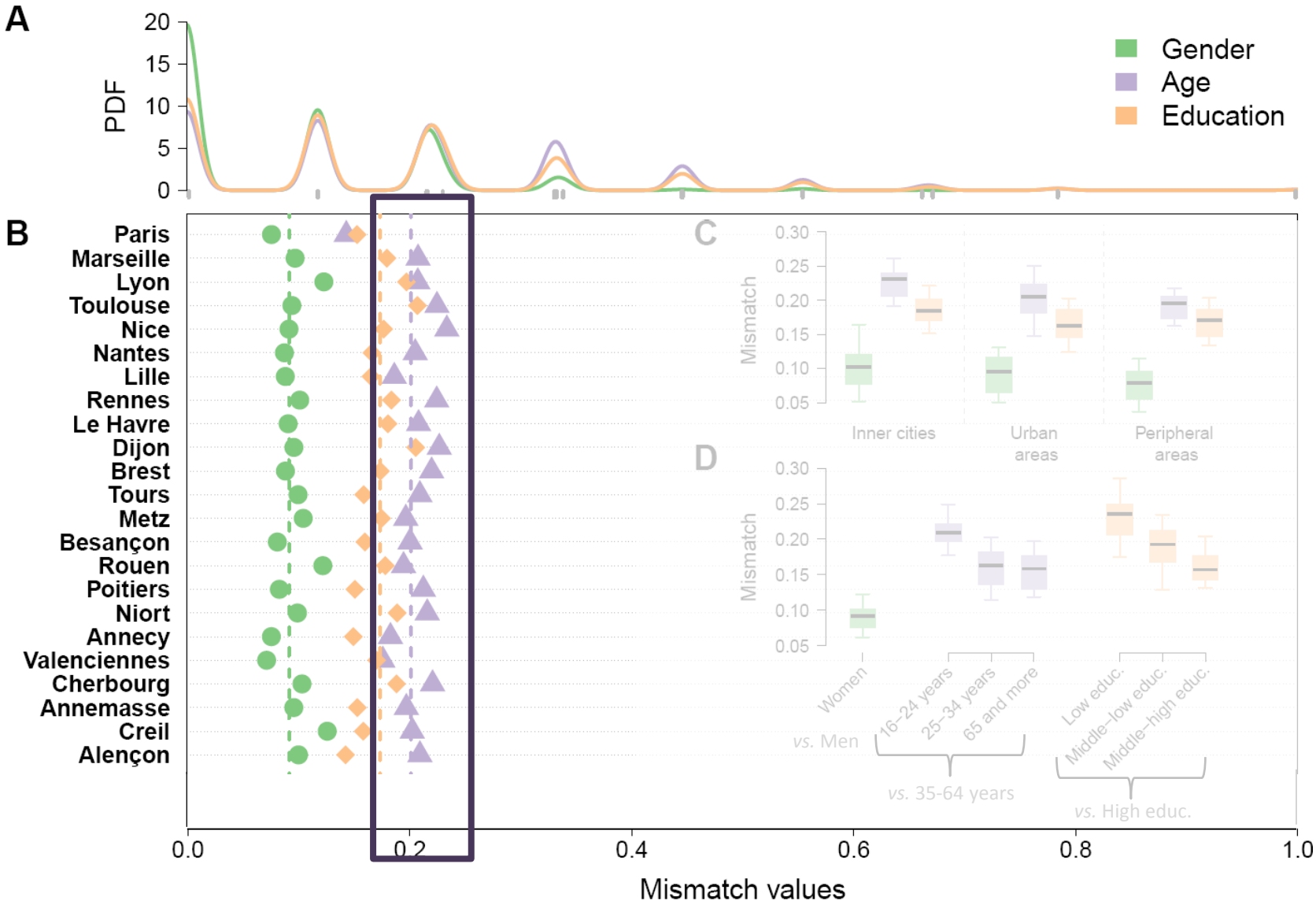

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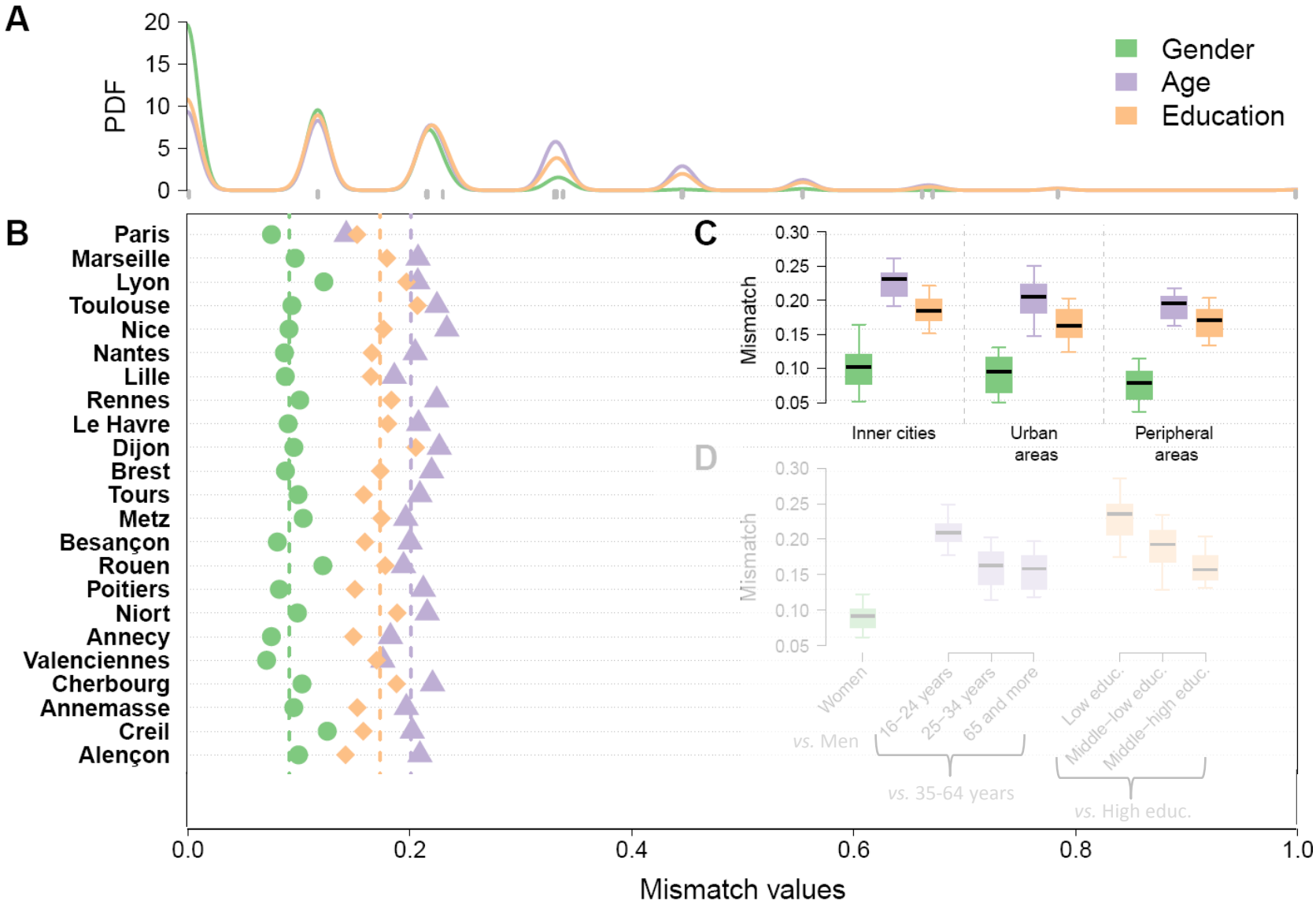

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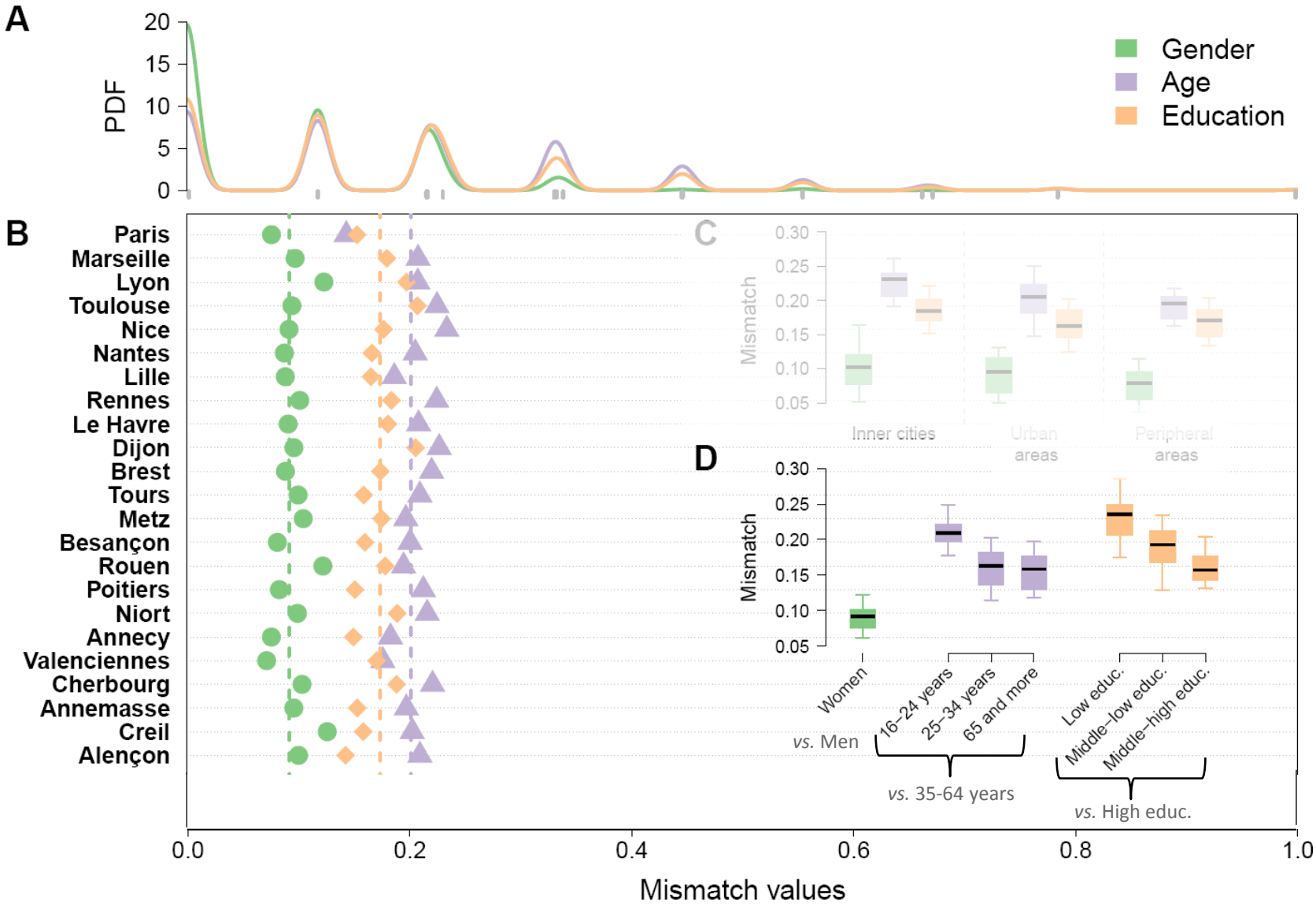

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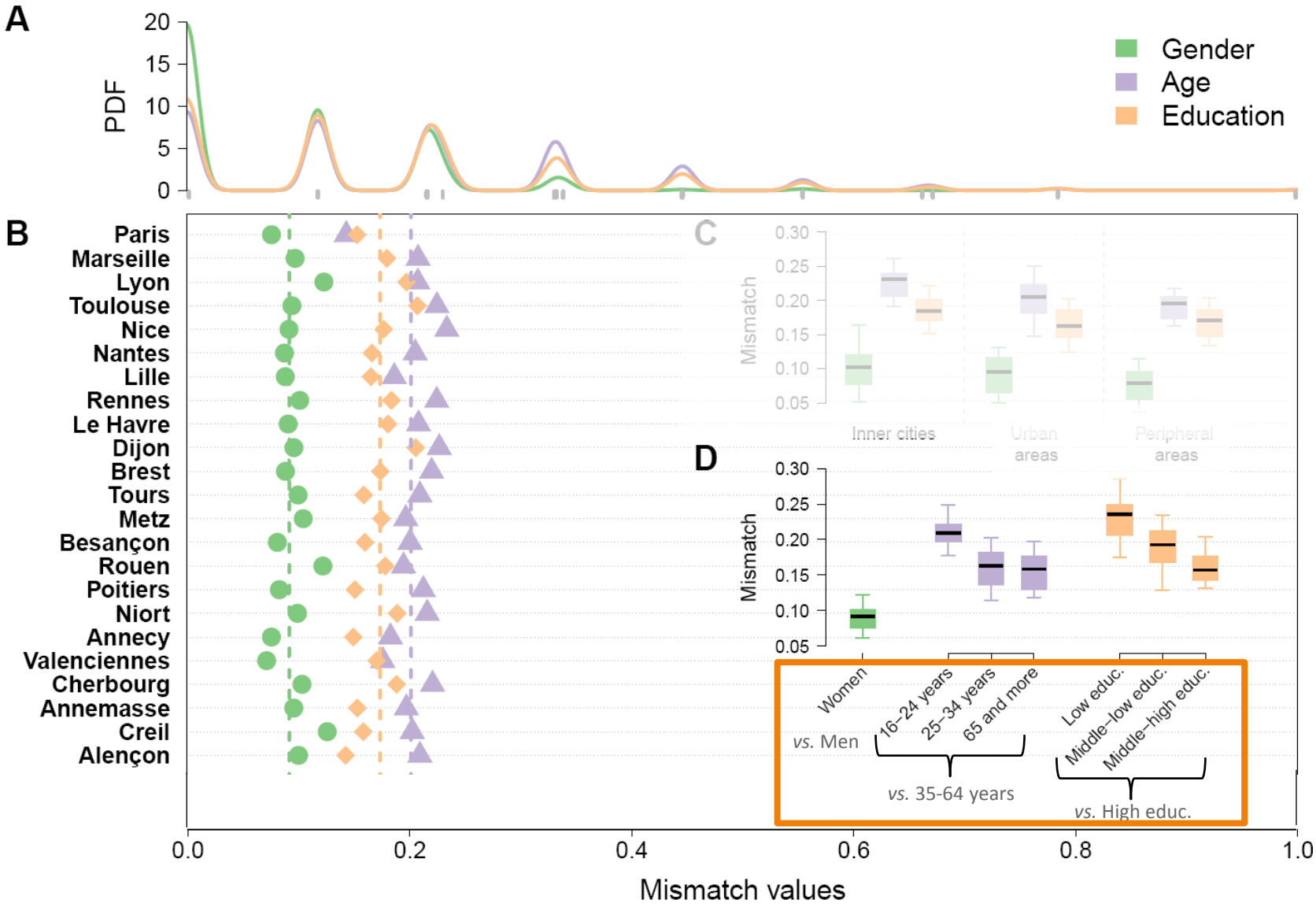

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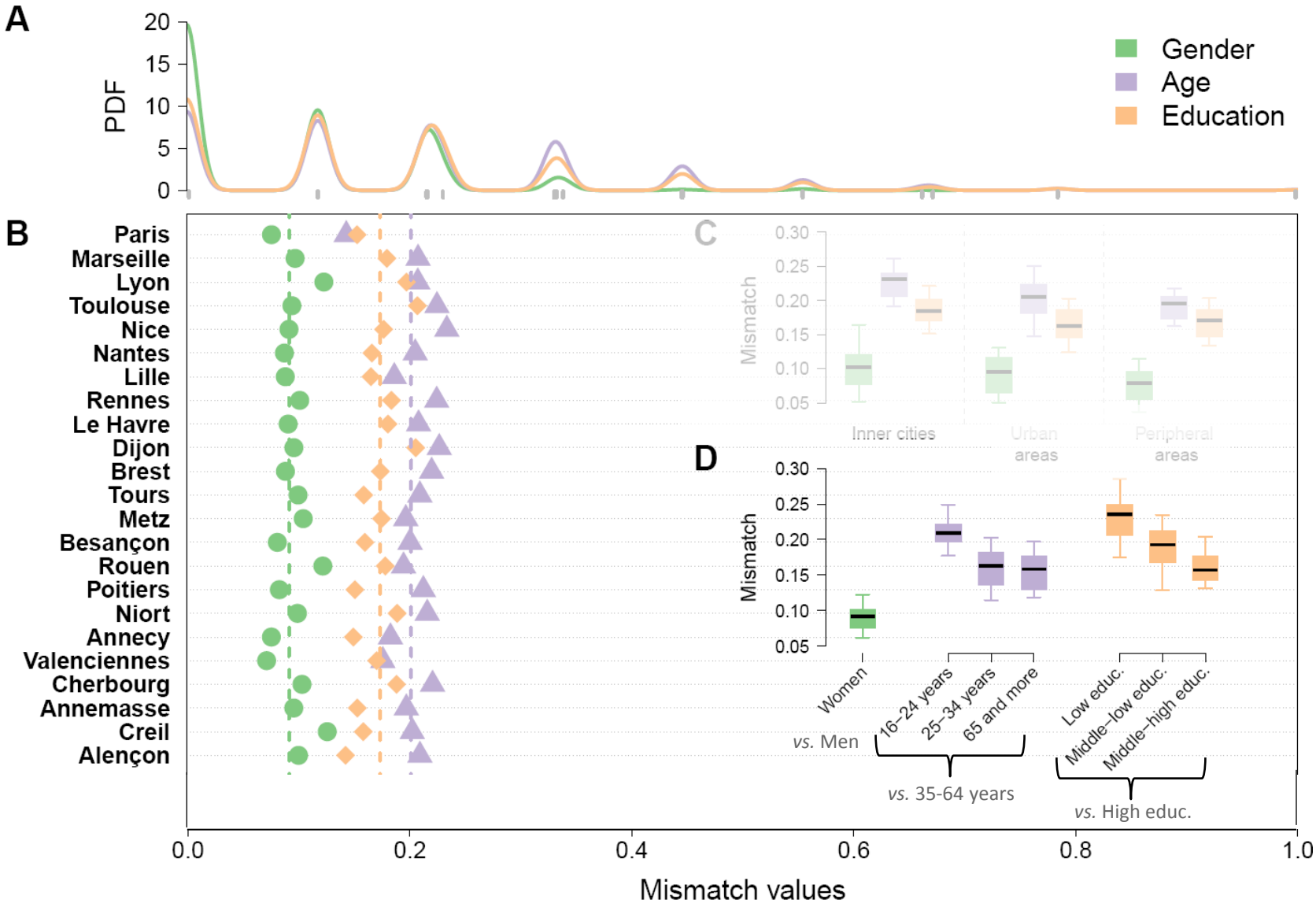
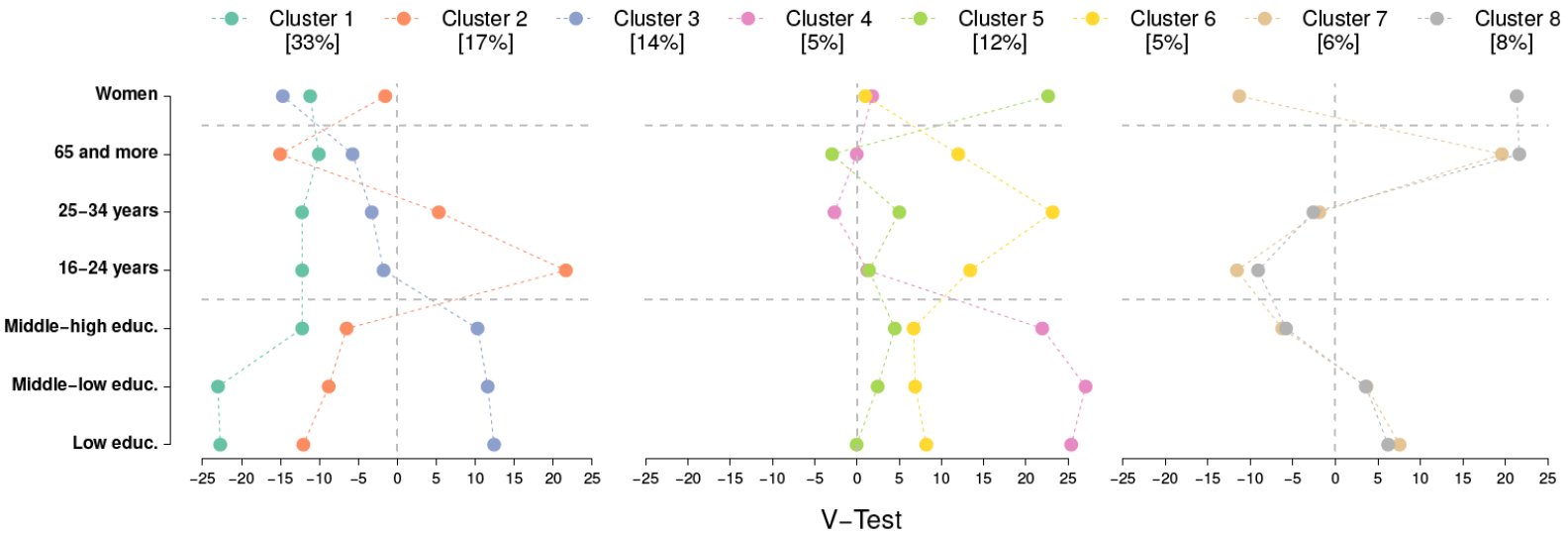
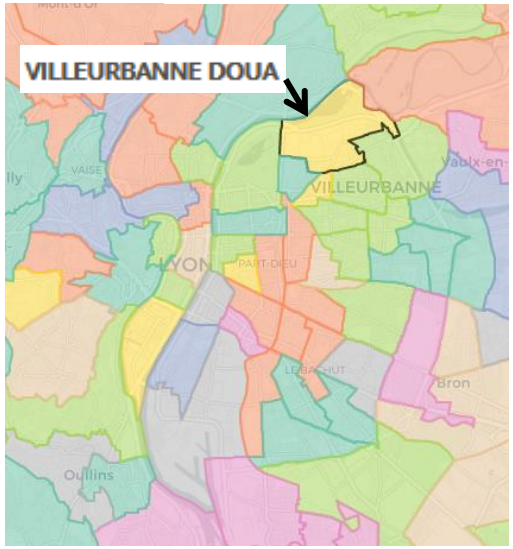
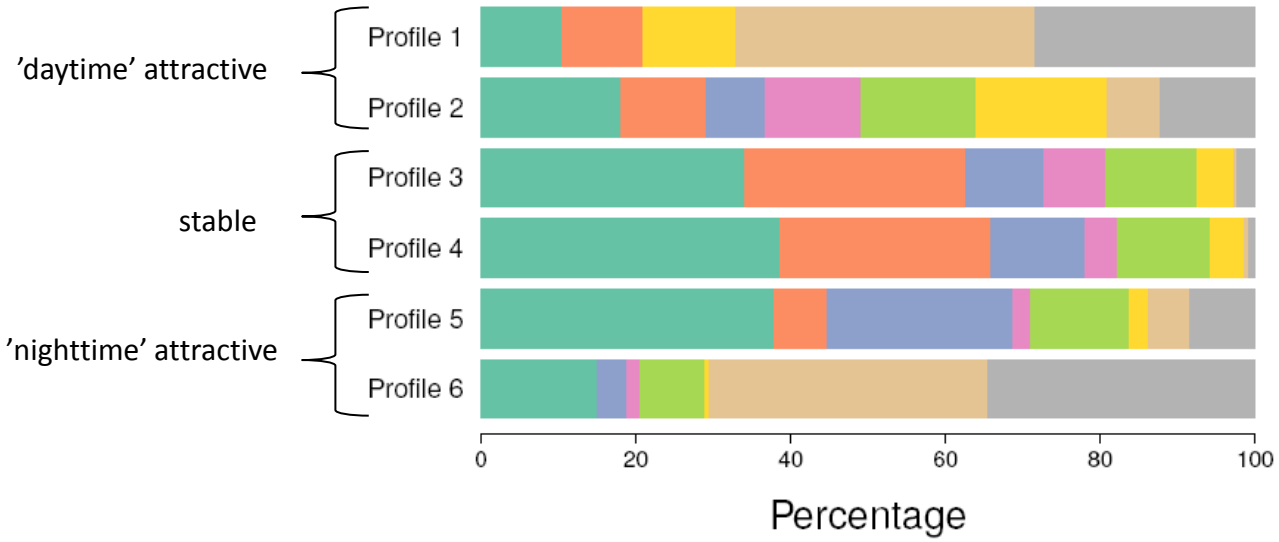


Combinations of mismatches in hourly profiles







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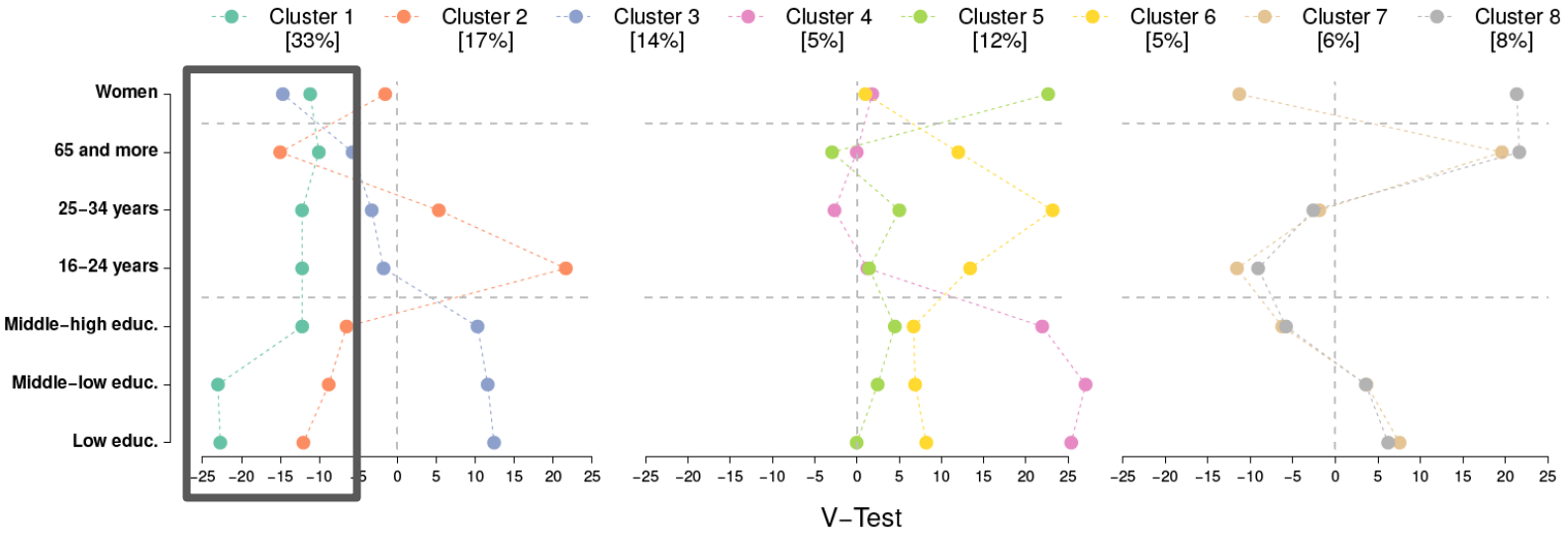

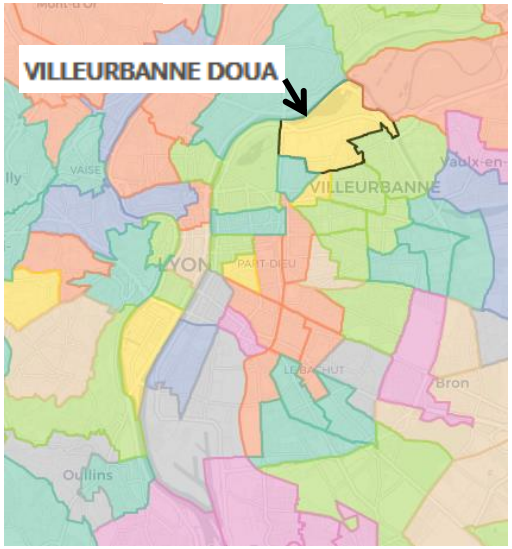

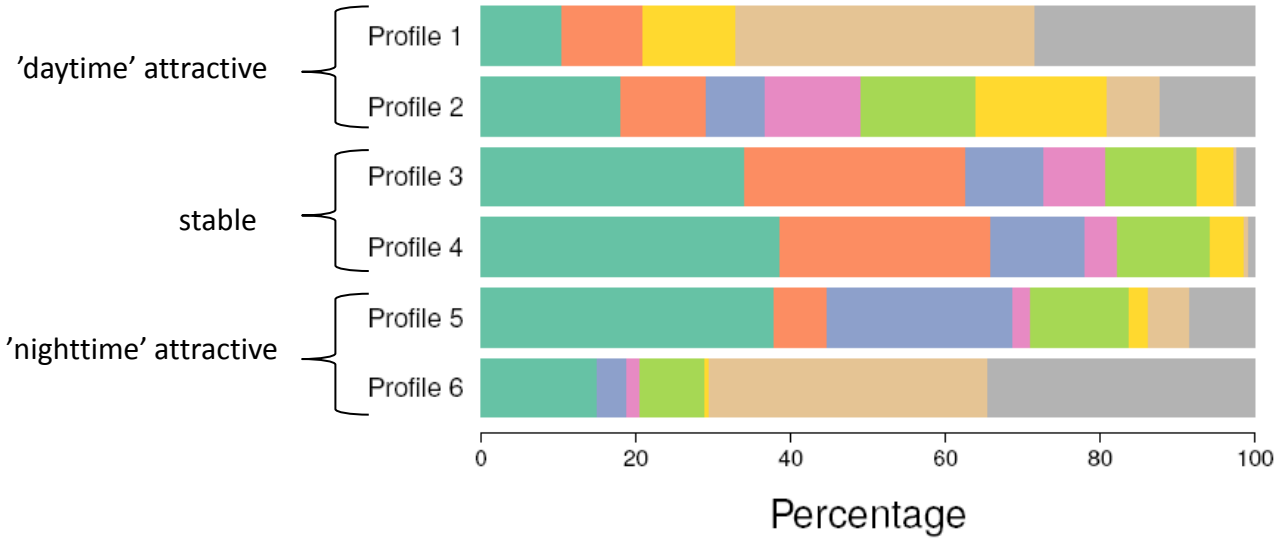

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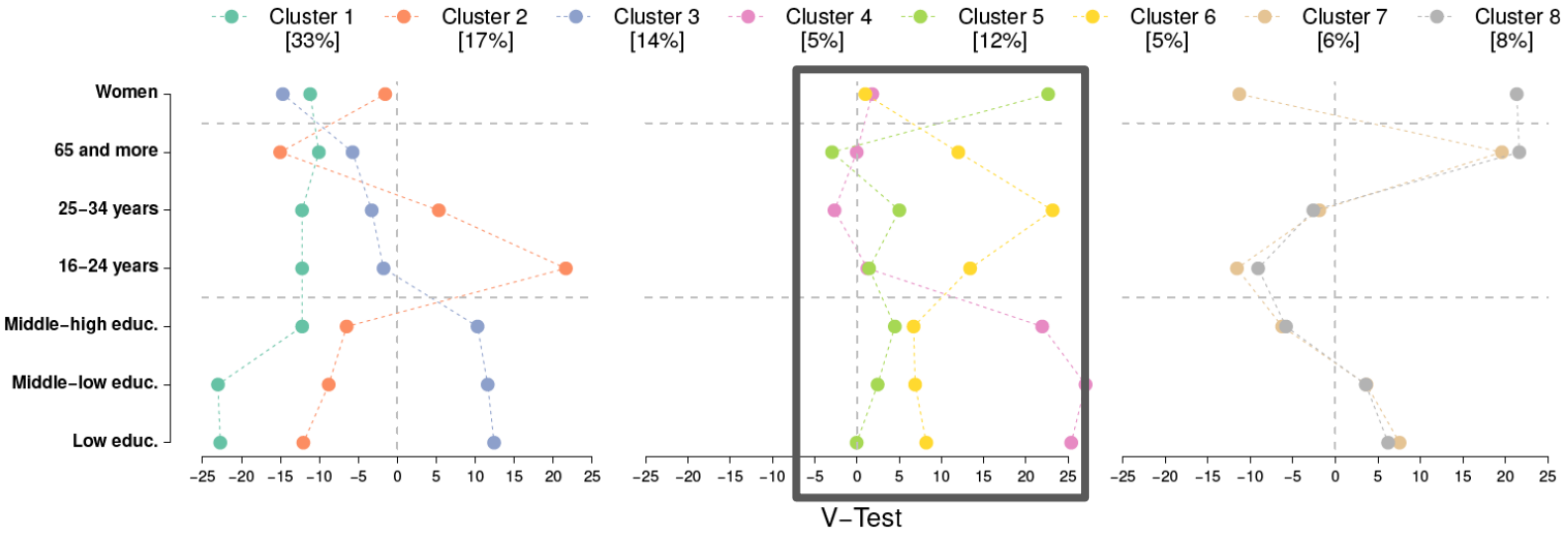

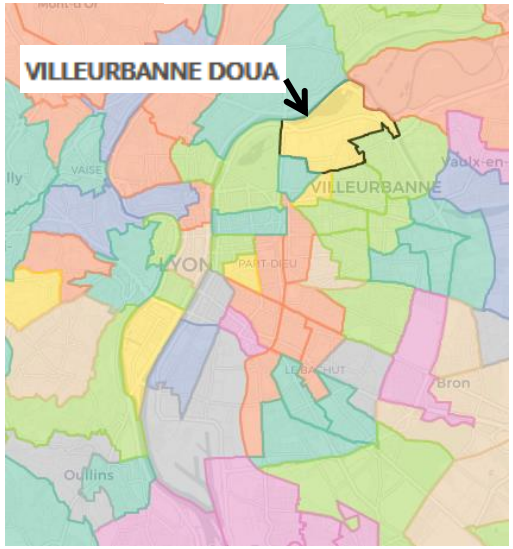

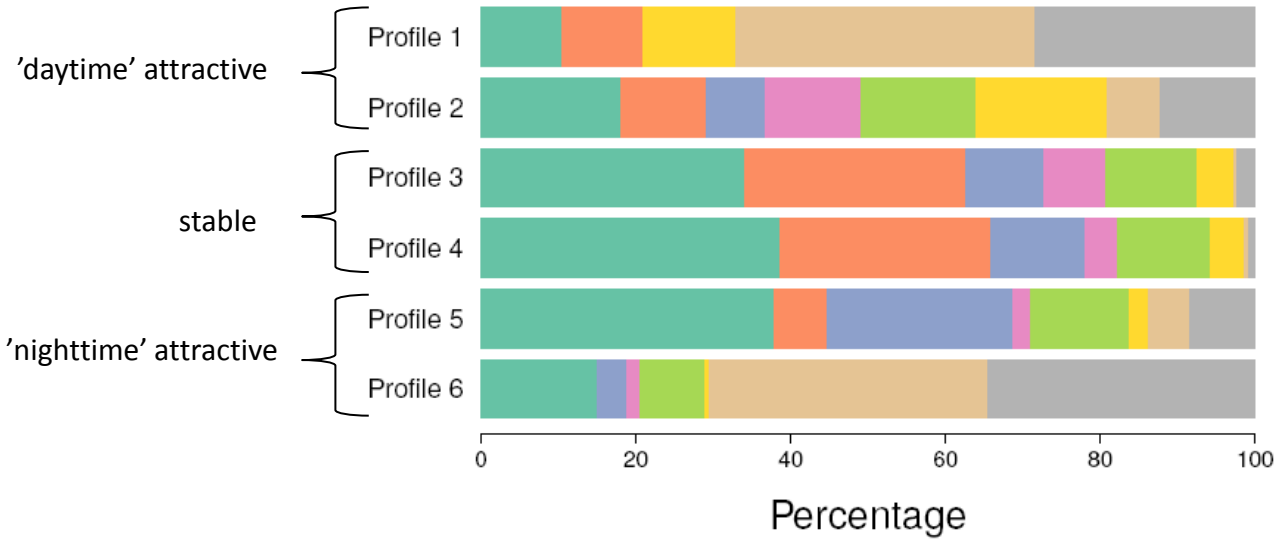

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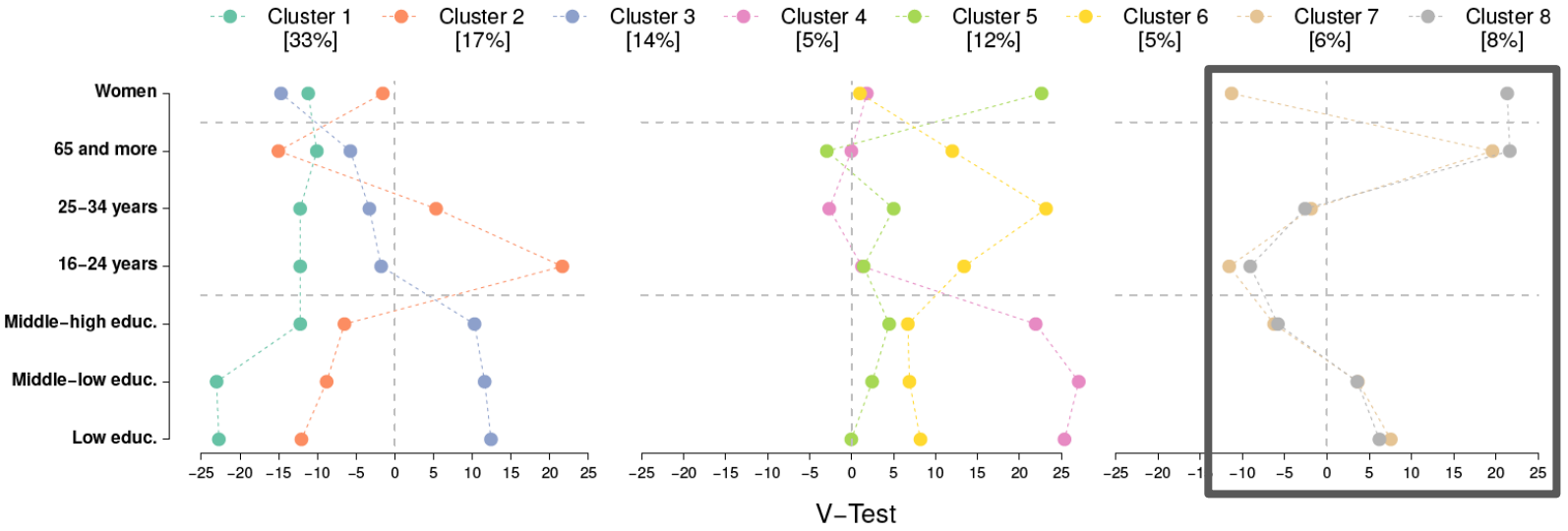
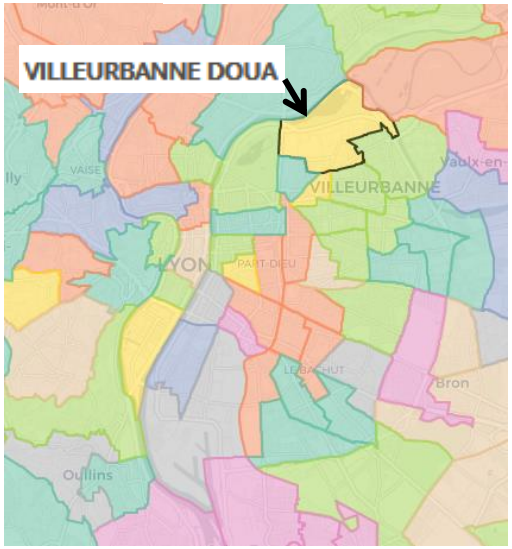
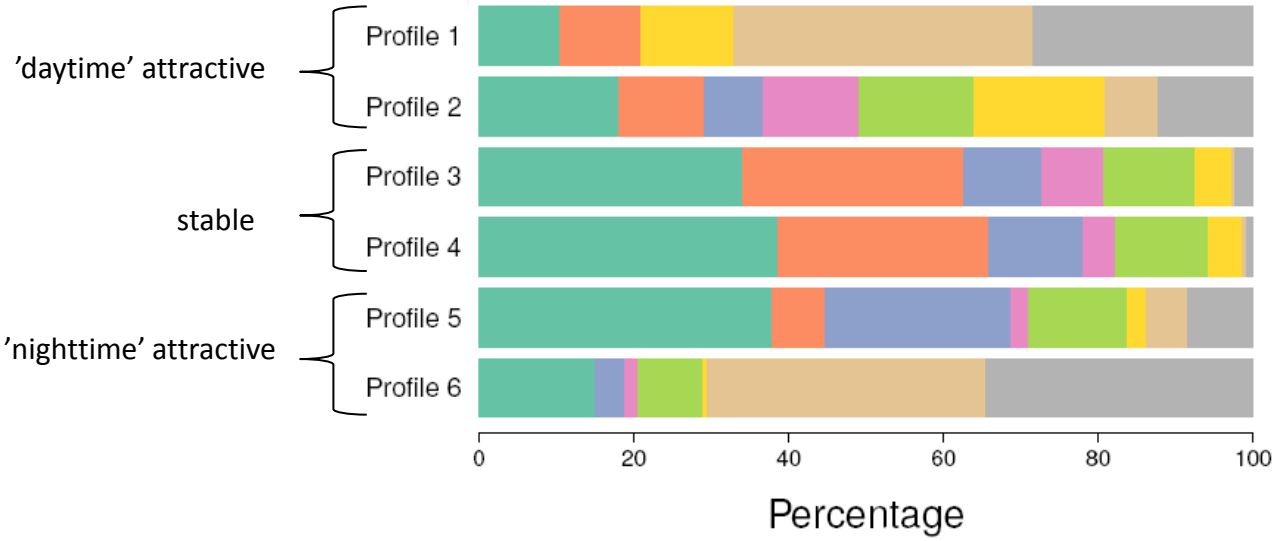


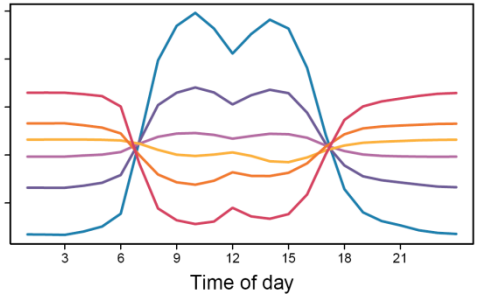


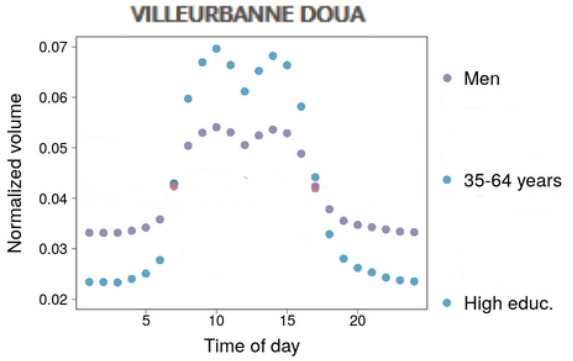


Mismatch in hourly profiles – Methods

DOMINANTS *versus* SUBORDINATES

Mismatch between the three '**dominants**' groups:
men, middle-age and high educational people





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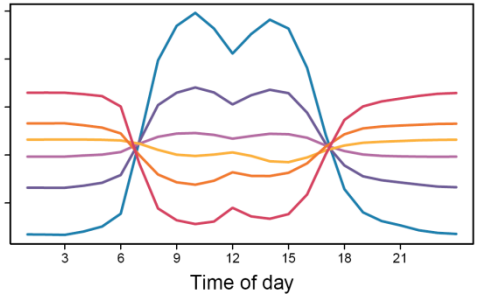

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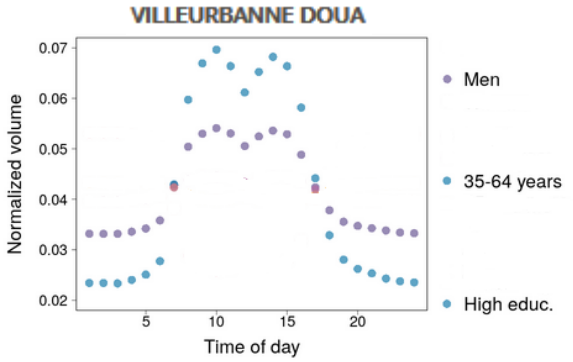

Mismatch between three '**subordinates**' groups:
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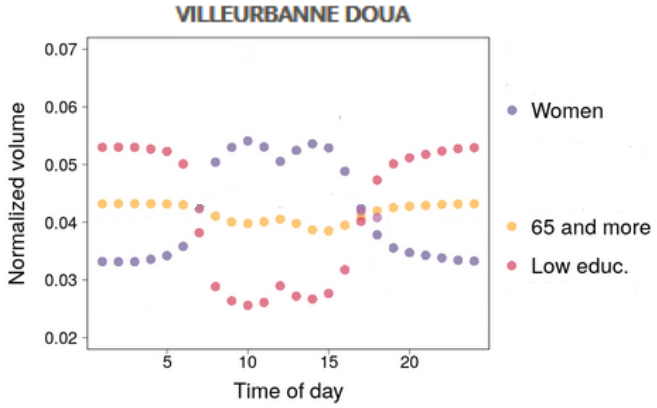
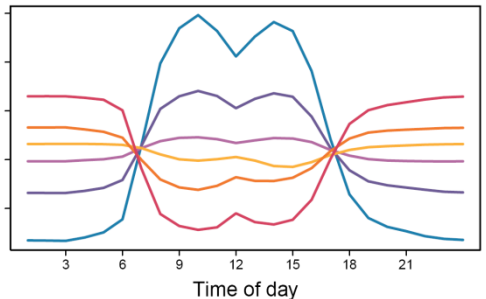


Mismatch in hourly profiles – Results

DOMINANTS *versus* SUBORDINATES

		Number of districts	**Dominants** *men, middle-age and high educational people*		**Subordinates** *women, elderly and low educated people*
			Average mismatch *(and standard deviation)* in hourly profiles		
	Per profiles (for the All population)				
'daytime' attractive	Profile 1	67	0.068 *(0.112)*	<	**0.273** *(0.134)*
	Profile 2	261	0.163 *(0.117)*	≈	0.168 *(0.1)*
stable	Profile 3	585	**0.125** *(0.109)*	>	0.09 *(0.09)*
	Profile 4	567	**0.125** *(0.104)*	>	0.084 *(0.077)*
'nighttime' attractive	Profile 5	901	0.11 *(0.087)*	≈	0.125 *(0.077)*
	Profile 6	180	0.052 *(0.074)*	<	**0.209** *(0.102)*



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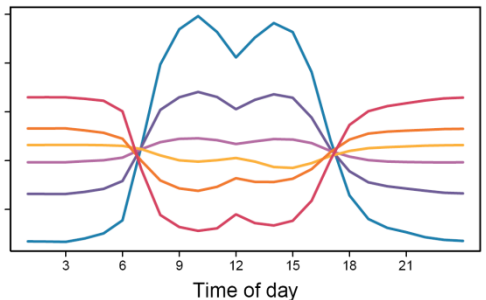

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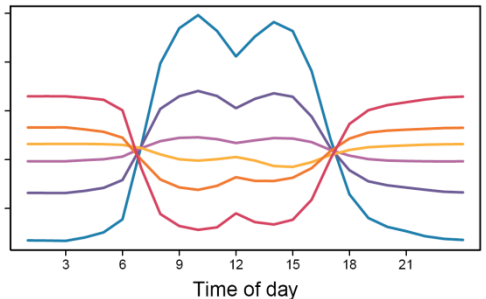
stable	Profile 3	585	**0.125** *(0.109)*	>	0.09 *(0.09)*
	Profile 4	567	**0.125** *(0.104)*	>	0.084 *(0.077)*
’nighttime’ attractive	Profile 5	901	0.11 *(0.087)*	≈	0.125 *(0.077)*
	Profile 6	180	0.052 *(0.074)*	<	**0.209** *(0.102)*



Mismatch in hourly profiles – Results

DOMINANTS *versus* SUBORDINATES

		Number of districts	**Dominants** *men, middle-age and high educational people*		**Subordinates** *women, elderly and low educated people*
			Average mismatch *(and standard deviation)* in hourly profiles		
	Per profiles (for the All population)				
'daytime' attractive	Profile 1	67	0.068 *(0.112)*	<	**0.273** *(0.134)*
	Profile 2	261	0.163 *(0.117)*	≈	0.168 *(0.1)*
stable	Profile 3	585	**0.125** *(0.109)*	>	0.09 *(0.09)*
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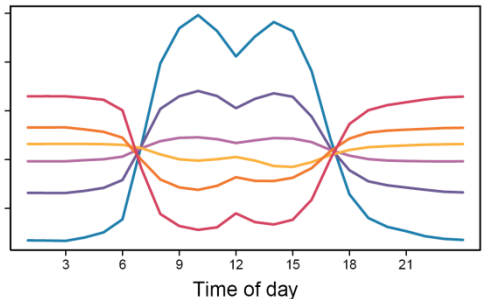

To resume

- It is especially in areas with strong increase or decrease of population during the day that hourly profiles
  - combine the largest dissimilarities within gender, age and educational subgroups
  - are widely more synchronous between ‘dominants’ subgroups than between ‘subordinates’ subgroups

- Empirical keys
  - to broaden the scope of segregation traditionally centered on residential areas
  - to improve knowledge of space-time (de)synchronization across gender, age and educational groups

- A step forward to distinguish
  - places where ’dominants’ groups are well-placed to join forces and perpetuate differential access to privileges,
  - or conversely places where ’subordinates’ groups face larger obstacles to make common causes and to get a convergence in their empowerment

Open science

- All data, code and materials are available
  - Initial **data** with hourly populations estimations
    - ✓ in the MOBILISCOPE platform - https://mobiliscope.cnrs.fr/en
    - ✓ also in a Zenodo repository - https://doi.org/10.5281/zenodo.4900655
  - **Procedures** in a public repo - https://gitlab.huma-num.fr/daycourse/intersectionality
  - **Findings** can be fully explored in a open dedicated cartographic platform http://shiny.umr-tetis.fr/Intersectionality
- Pre-print paper - https://arxiv.org/abs/2106.15492

UrbanSys 2021, Lyon

INTERSECTIONAL APPROACH OF EVERYDAY GEOGRAPHY

Julie Vallée - julie.vallee@parisgeo.cnrs.fr

Maxime Lenormand - maxime.lenormand@inrae.fr

cnrs

Géographie-cités
UMR 8504

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