Mobility and COVID-19 Spread: Solving the Puzzle

A Nonparametric Method with Applications on Montreal, Toronto, and New York

Yigit Aydede (SMU) & **Mutlu Yuksel** (DAL)

Research Portal on Machine Learning for Social and Health Policies – MLPortal

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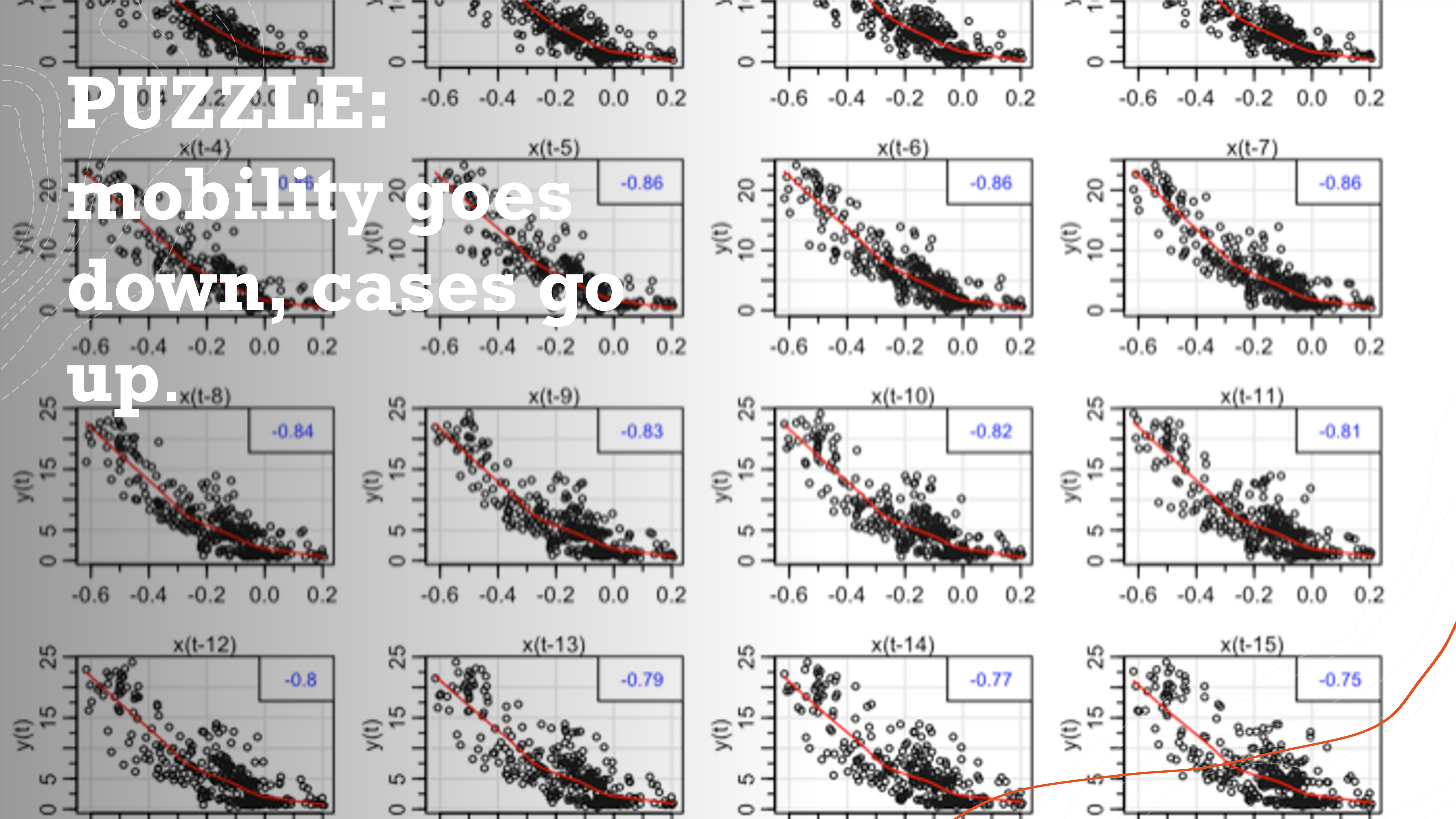
Non-Pharmaceutical Interventions:

Mobility Restrictions

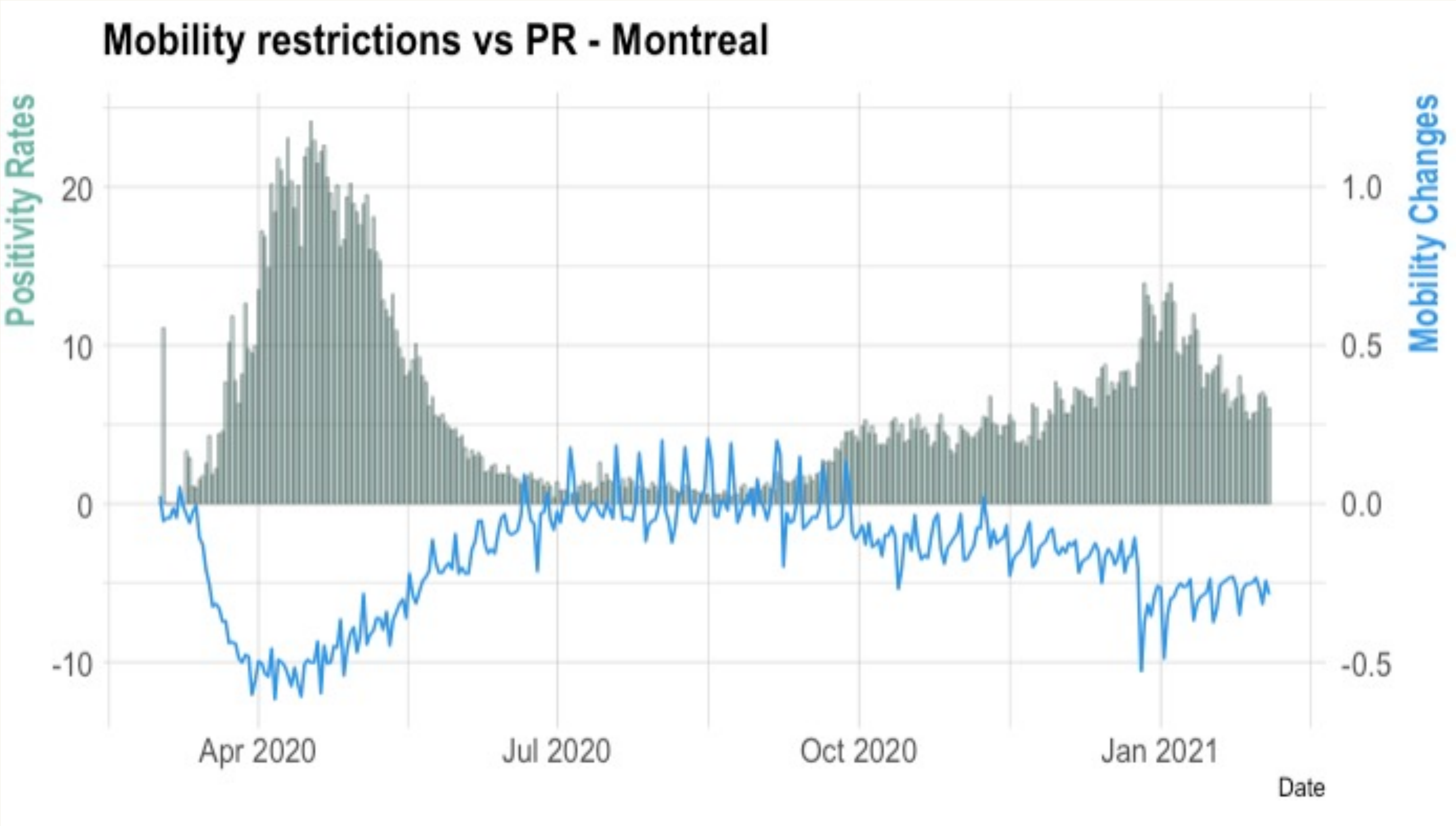
- Mobility restrictions are the only effective tool to control for the viral transmission so far.
- None of the studies able to quantify the effectiveness of NPI's that can be used to measure:
  - **When the varying delays in its effect on the spread are identified properly, what would be the overall effect of mobility restrictions?**
  - **If mobility restrictions have any effect; how long does it take to start seeing some positive effects?**
- The overall social response to the COVID-19 pandemic consisted of a mix of voluntary and government mandated behavioral changes.
- Without accounting for this dynamic structure, a naive calculation of correlations with any level of lagged mobility variations shows a strong negative relationship: **as the mobility goes down, cases go up**.

PUZZLE: mobility goes down, cases go up.



Data: Positivity Rates and Mobility Changes

- Three major cities: **Montreal, Toronto,** and **New York City**.
- We use **positivity rates** (PR) that reflect the spread.
- Facebook mobility data which measures **positive or negative changes in movement** relative to baseline.



Three time-varying metrics that measure the effect of social mobility on the spread

01

The **correlation** that reflects the nature of relationship between mobility restrictions and positivity rates.

02

The **elasticity** that measures how effectively that relationship is utilized to curb the spread.

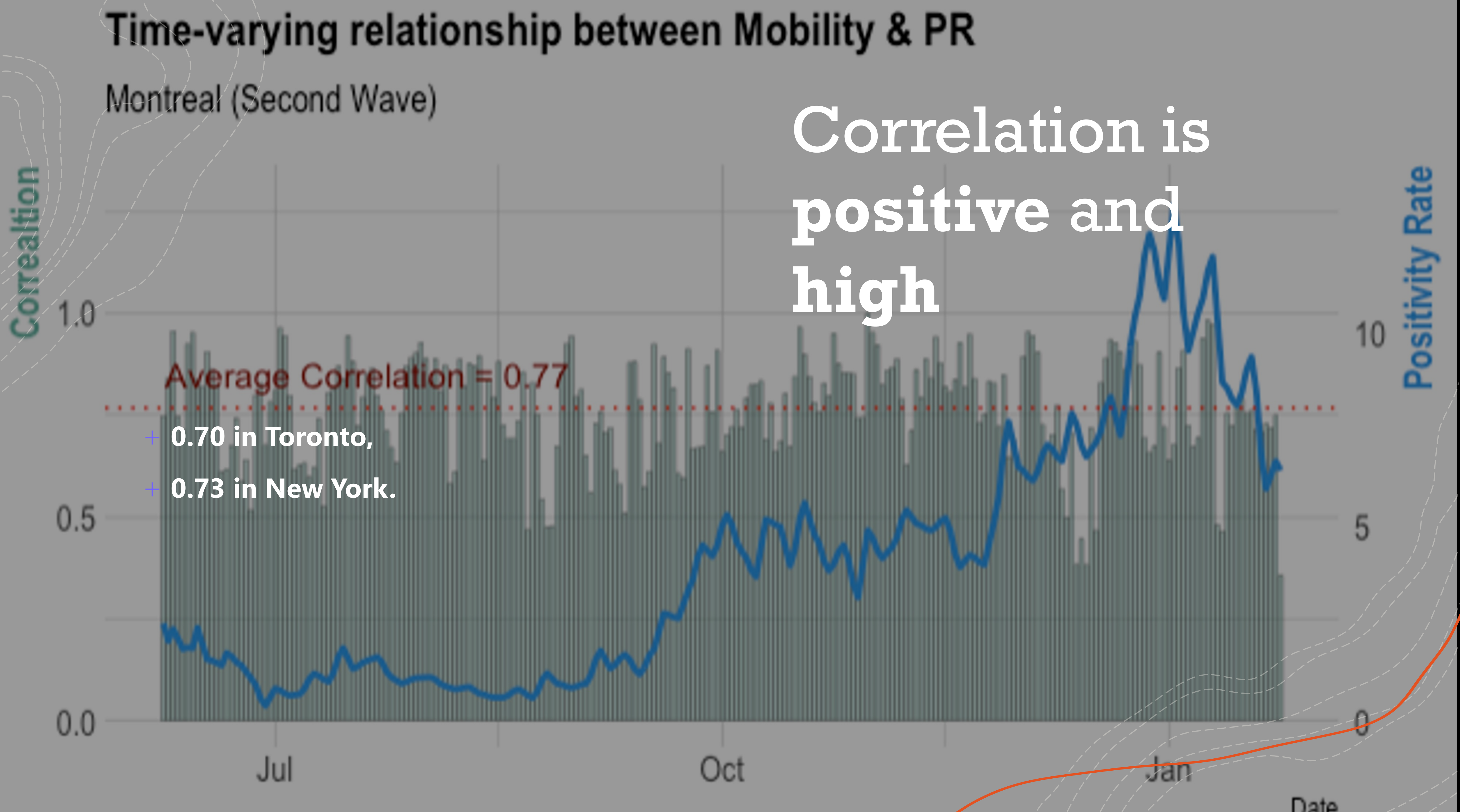
03

The average **delay** in the effect of these restrictions that reflects how efficient the contact tracing is.

Dynamic Functional Connectivity (DFC)

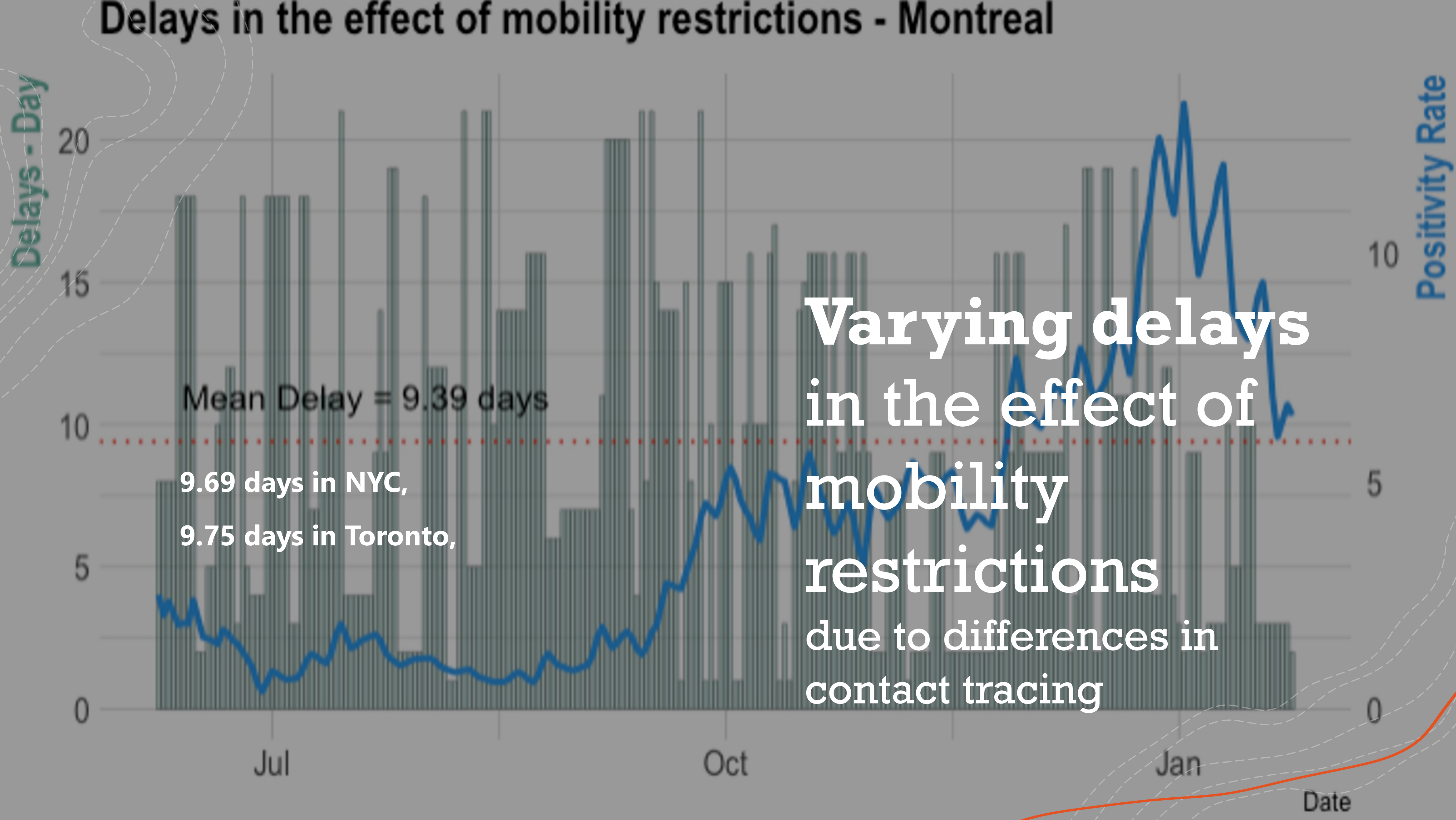
- It refers to the observed phenomenon that *functional connectivity changes over a short time*.
- It has been suggested to be a more accurate representation of functional brain networks and the main tool in neuroimaging.
- We apply a modified DFC to the relationship between restrictions and PR by using advance machine learning methods.

The **first methodological framework** to identify the local differences in the efficacy of mobility related public health policies.



Correlation is **positive** and **high**

- 0.70 in Toronto,
- 0.73 in New York.



9.69 days in NYC,

9.75 days in Toronto,

Varying delays in the effect of mobility restrictions

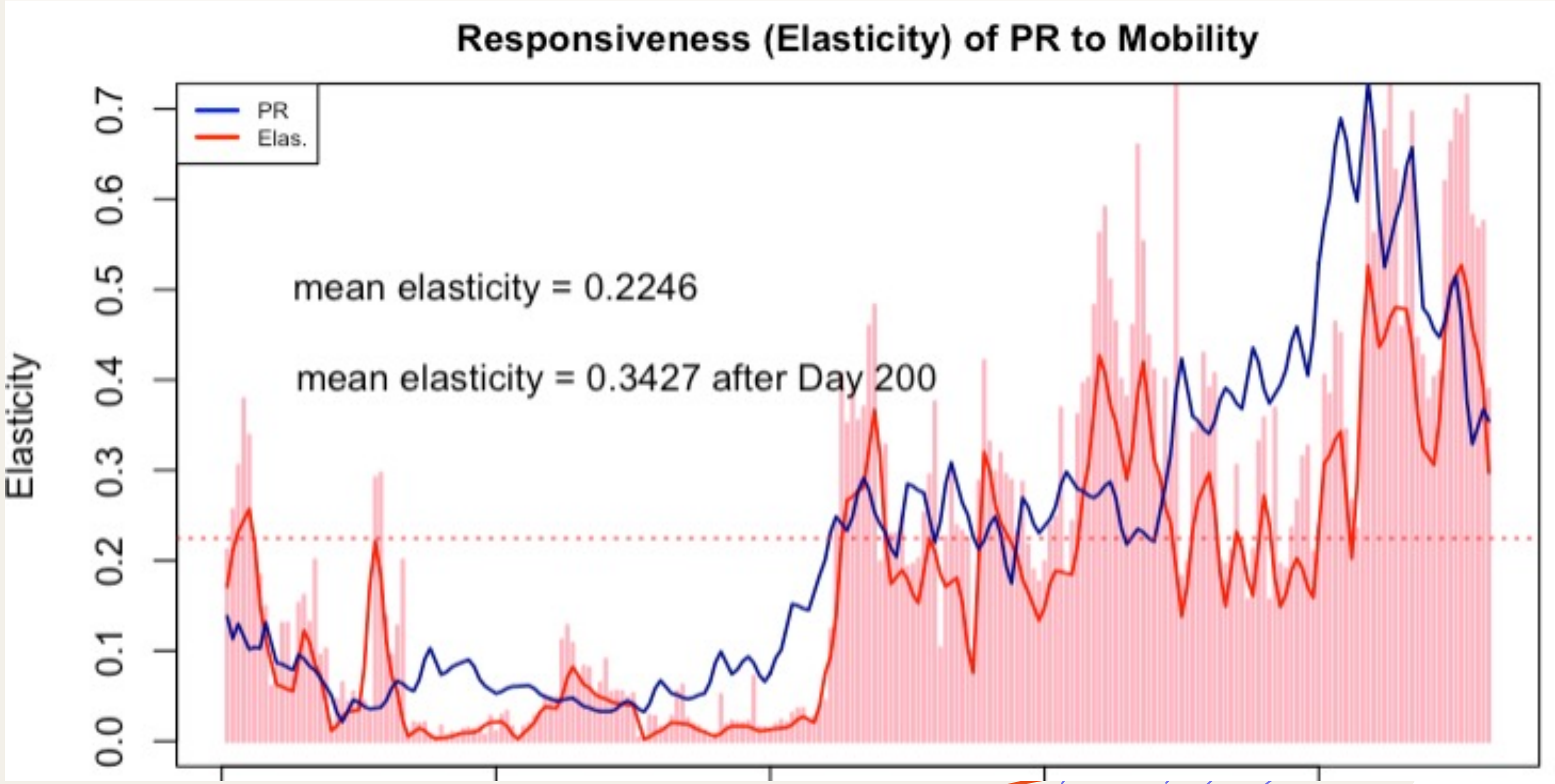
due to differences in contact tracing

Restrictions are **not effective in Montreal**

Correlation measures the nature of a relationship; **Elasticity** measures how effectively that relationship is utilized.

Elasticities: **0.34**, **0.79**, and **0.62**, Montreal Toronto and NYC, respectively during the 2nd wave

10% fall in mobility reduces PR **3.4%** in **Montreal** and **7.9%** in **Toronto.**



What's different in Montreal?

Our counter-factual simulation shows that:

- **Significantly lower public sensitivity** to COVID-19,
- **Insufficient reduction in mobility** in terms of its speed and magnitude.

When PR rates are very low at the onset, **the public orders for mobility restrictions may have a very poor effect** on the spread