

Mobility and COVID-19 Spread: Solving the Puzzle

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

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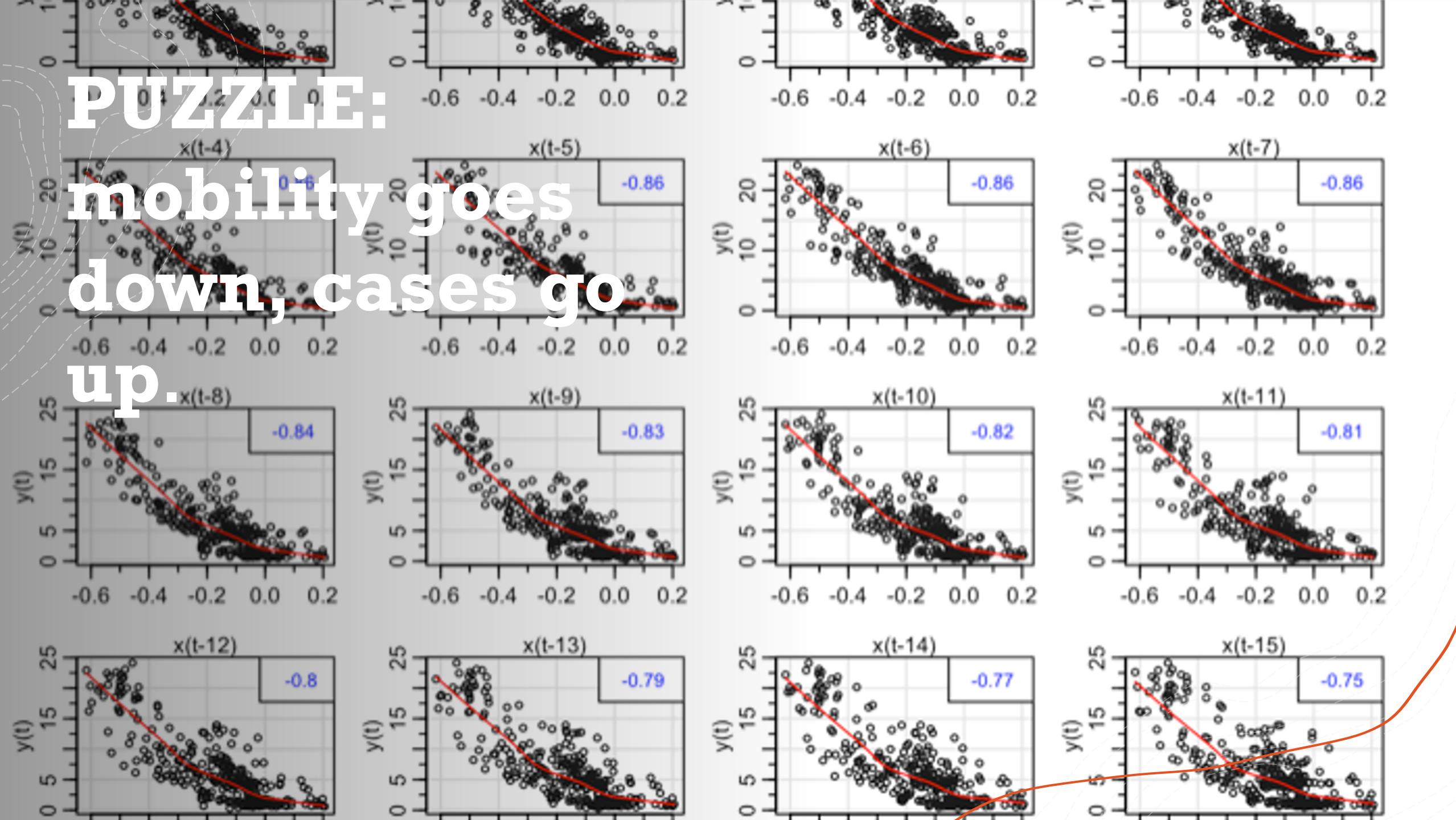
# Non- Pharmaceutical Interventions:

## 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.**

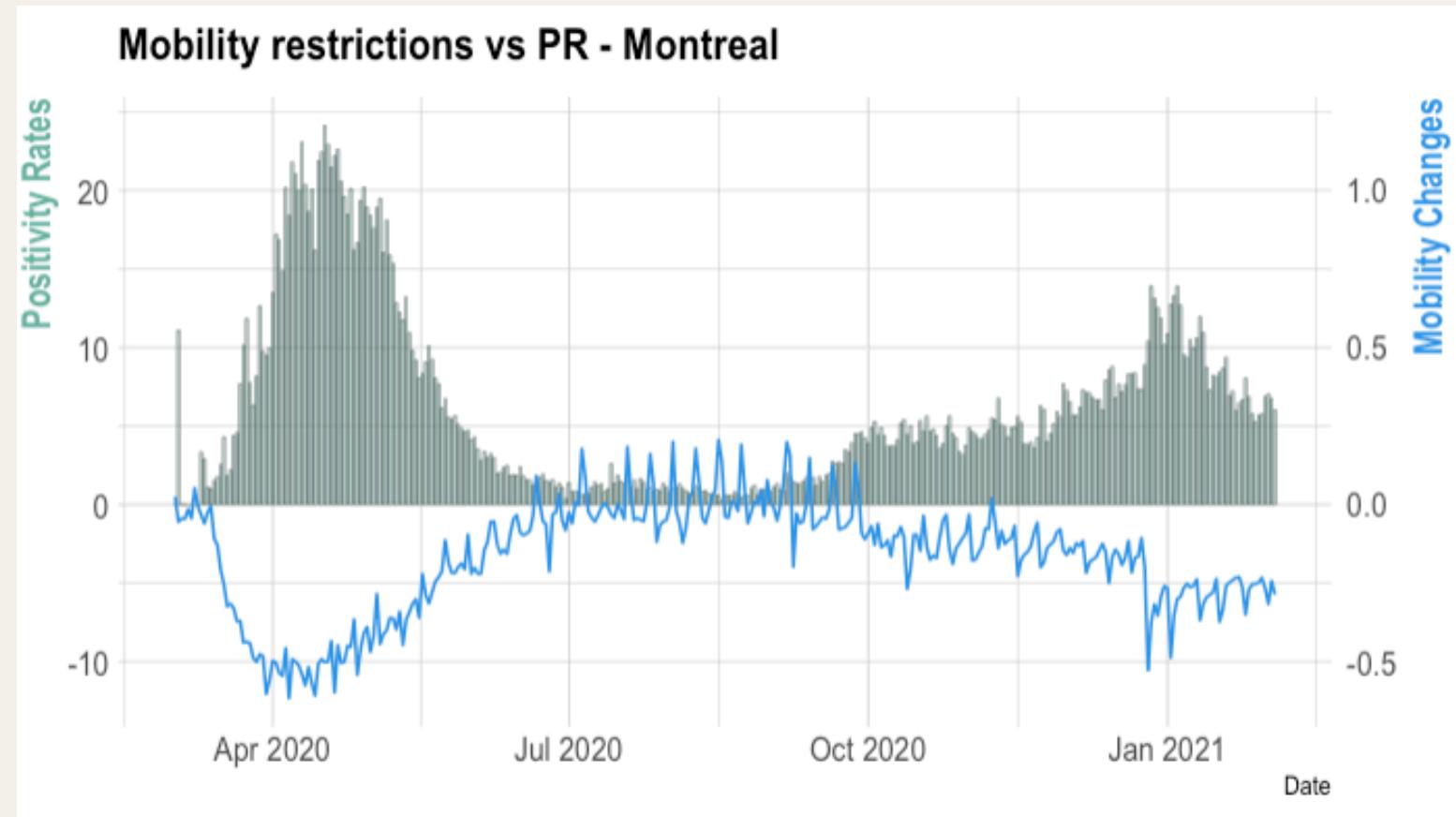
# PUZZLE:

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.

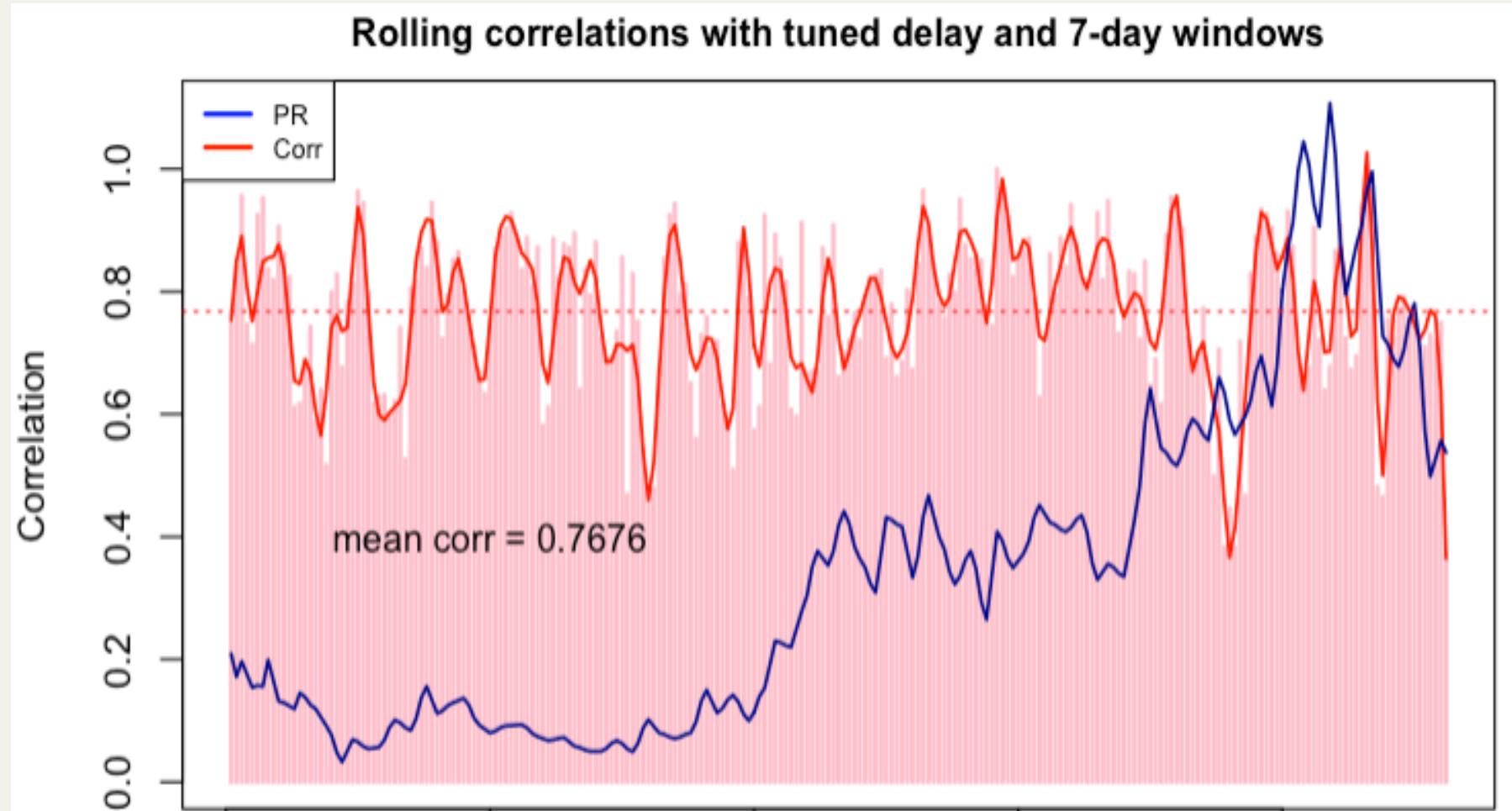
# Dynamic Functional Connectivity (DFC)

- + 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

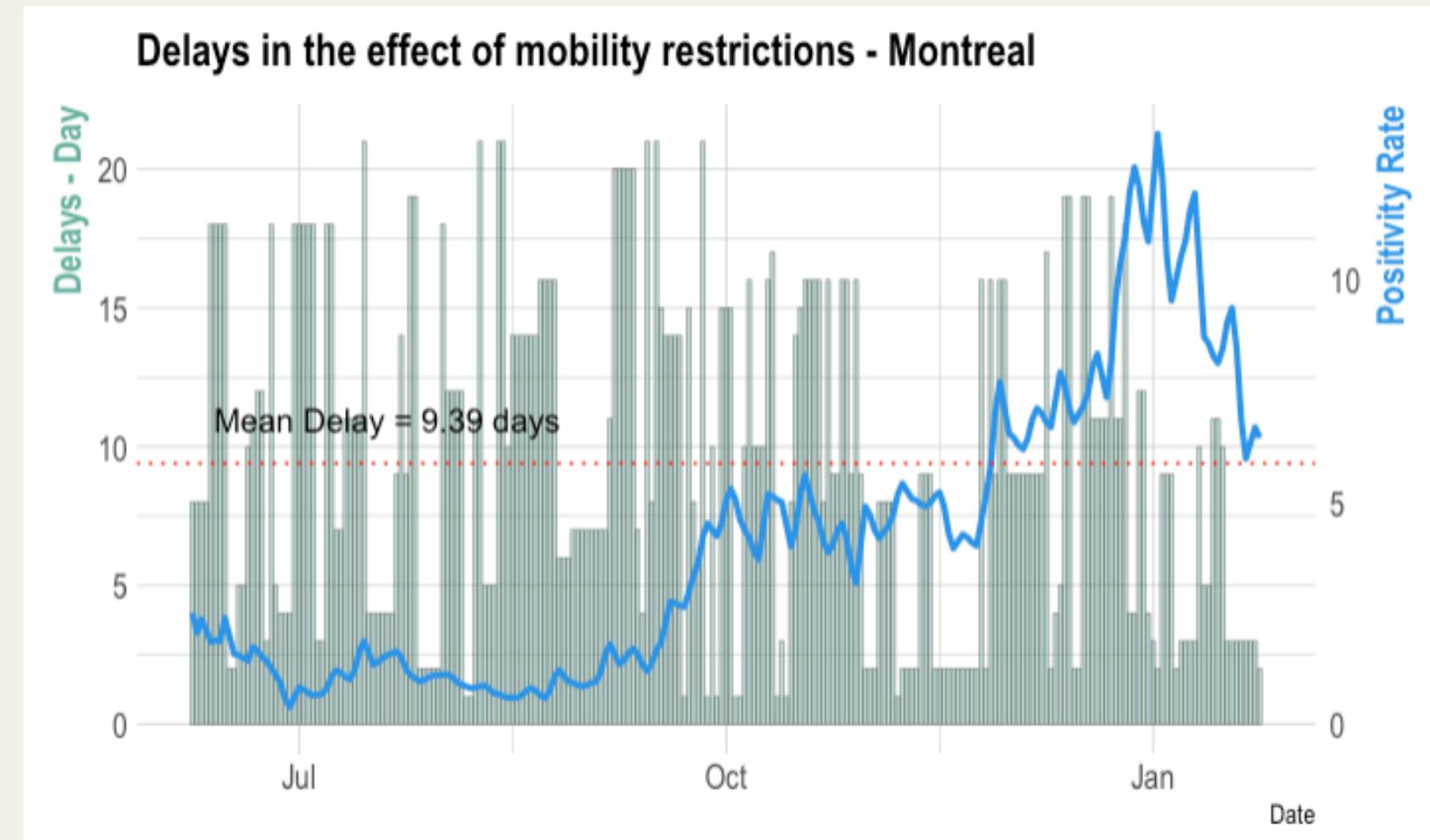
+ 0.77 in Montreal,  
+ 0.70 in Toronto,  
+ 0.73 in New York.



# Varying delays in the effect of mobility restrictions

We observe the *immediate effects* of mobility when contact tracing is effective.

- + 9.69 days in NYC,
- + 9.75 days in Toronto,
- + 9.39 days in Montreal

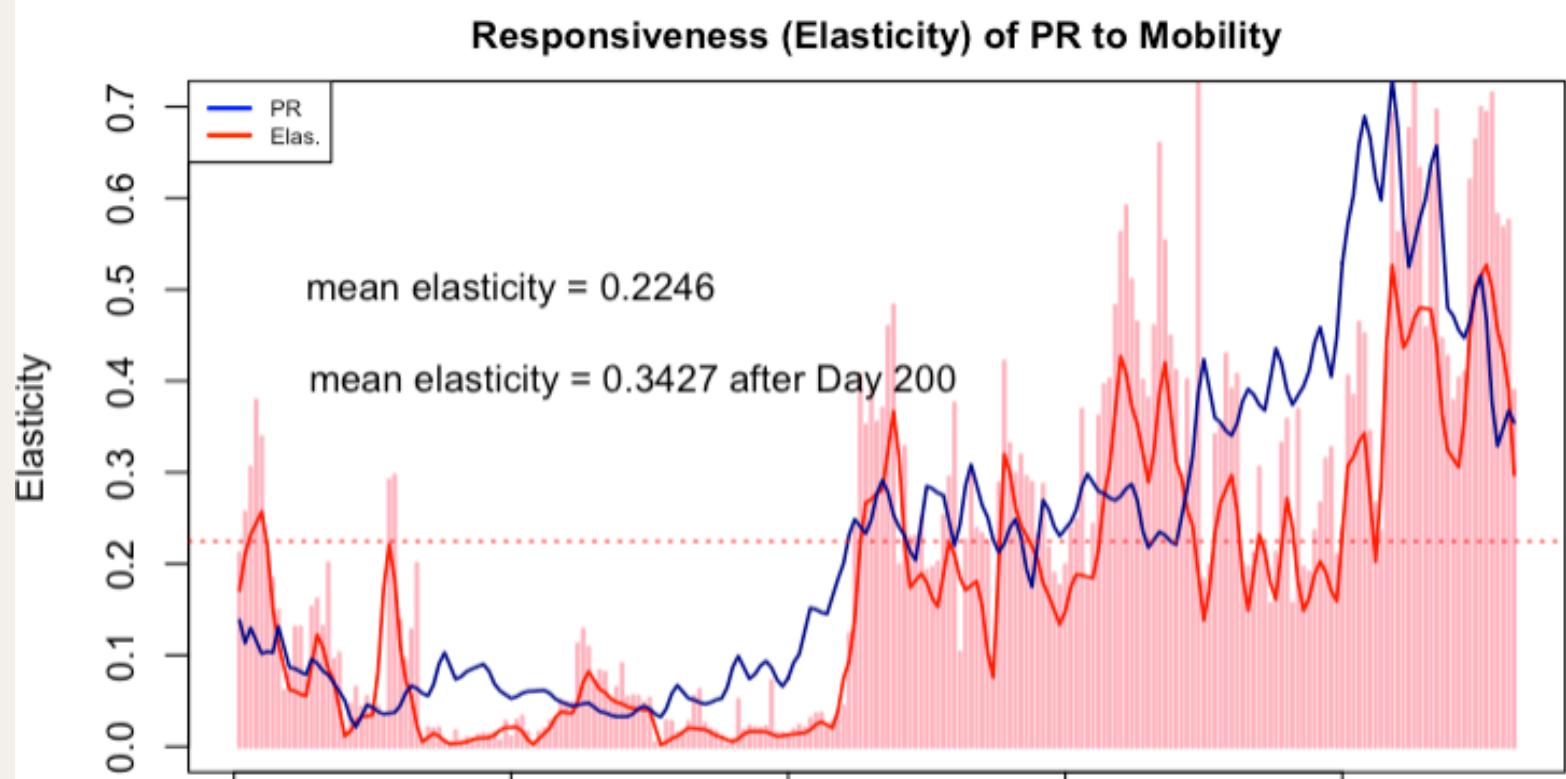


# Restrictions are **not effective** in Montreal

**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 2<sup>nd</sup> 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