

Introduction

Ride-sourcing companies provide pre-arranged or on-demand transportation service for compensation.

Objective

Analyze the spatial structure of ride-sourcing operational and driver performance variables to support the need for new pricing strategies.

Contributions

- Empirical evidence of spatial and temporal variation of driver productivity variables as a function of trip destination.
- Temporal and spatial evaluation of different ride-sourcing operational measures and search frictions in Austin, Texas.
- Implementation of a spatial denoising methodology to analyze high-definition spatial variables.

Methodology

Ride-Sourcing Data

Austin-based TNC (Ride Austin) trips during the period that Uber and Lyft were out of the city - from September 1, 2016, to April 13, 2017.

- Space: data is summarized over 1,305 traffic analysis zones (TAZs).
- Time: Weekday AM-peak, PM-peak, off-peak, and Weekend.

Description of variables

- Operational (based on trip origin)

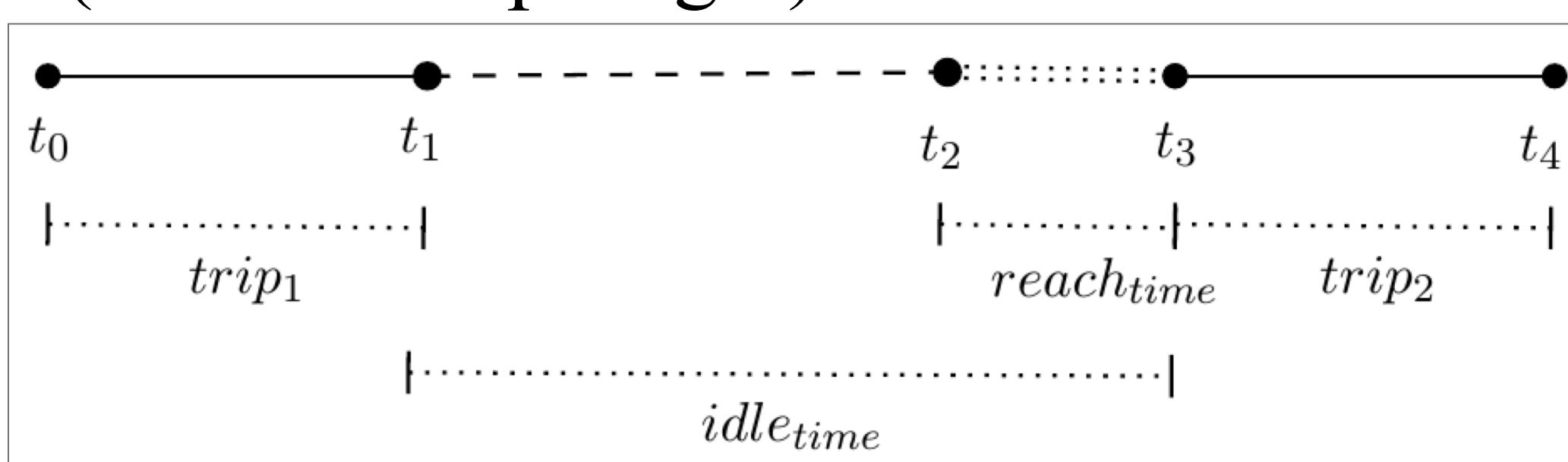


Figure: Driver time diagram

- Productivity, CBD-origin trips only (based on trip destination)

$$Prod. A = \frac{fare_{trip1}}{t_1}$$

$$Prod. B = \frac{fare_{trip1}}{t_3}$$

$$Prod. C = \frac{fare_{trip1} + fare_{trip2}}{t_4}$$

Spatial Smoothing Approach

Analyzing operational and performance variables at a high-definition spatial level requires additional data analytics methods. We propose the use of a spatial smoothing or denoising technique that allows fine resolution analysis and compensates for the inherent sampling noise.

Smoothing

Assume that we have observations y_i , each associated with a vertex $s_i \in \mathcal{V}$ in an undirected graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ with node set \mathcal{V} and edge set \mathcal{E} .

$$y_i = x_i + \varepsilon_i, i = 1, \dots, n$$

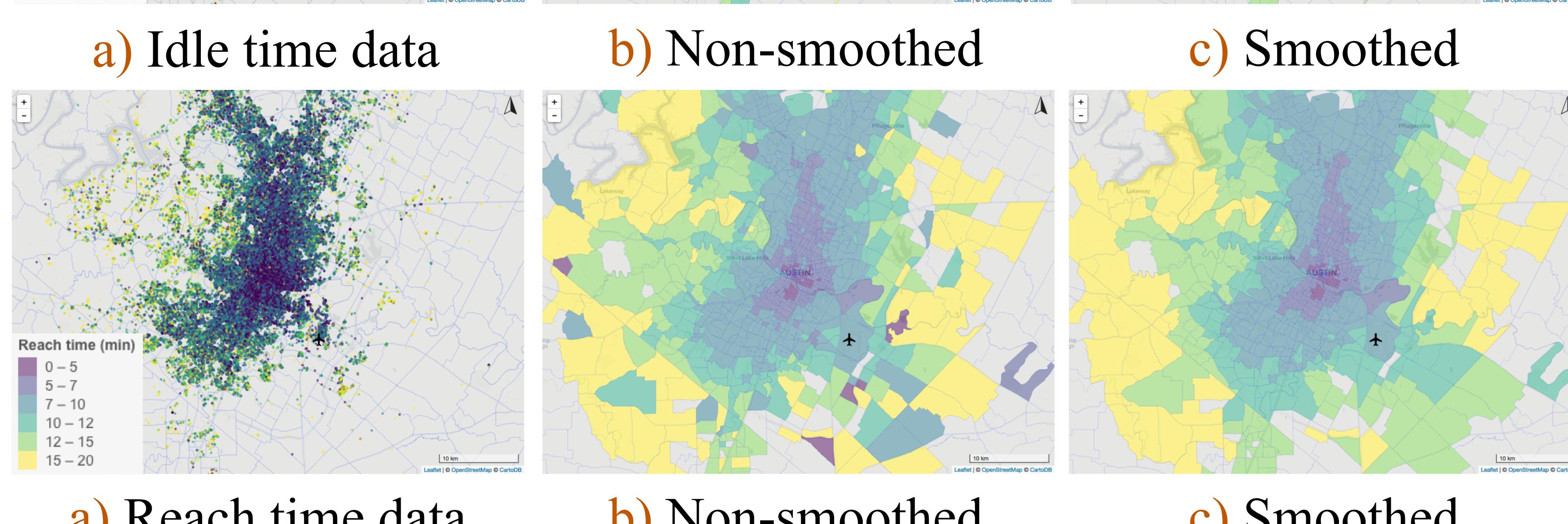
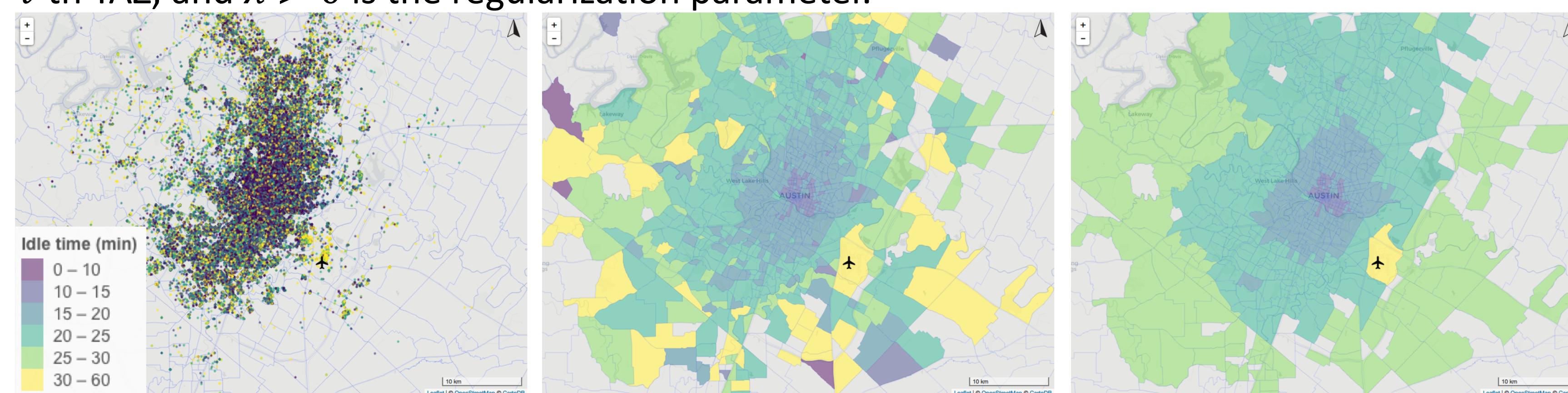
where, x_i is the “true” denoised signal and ε_i is mean-zero error. **Goal:** find x .

Graph-Fused Lasso (GFL)

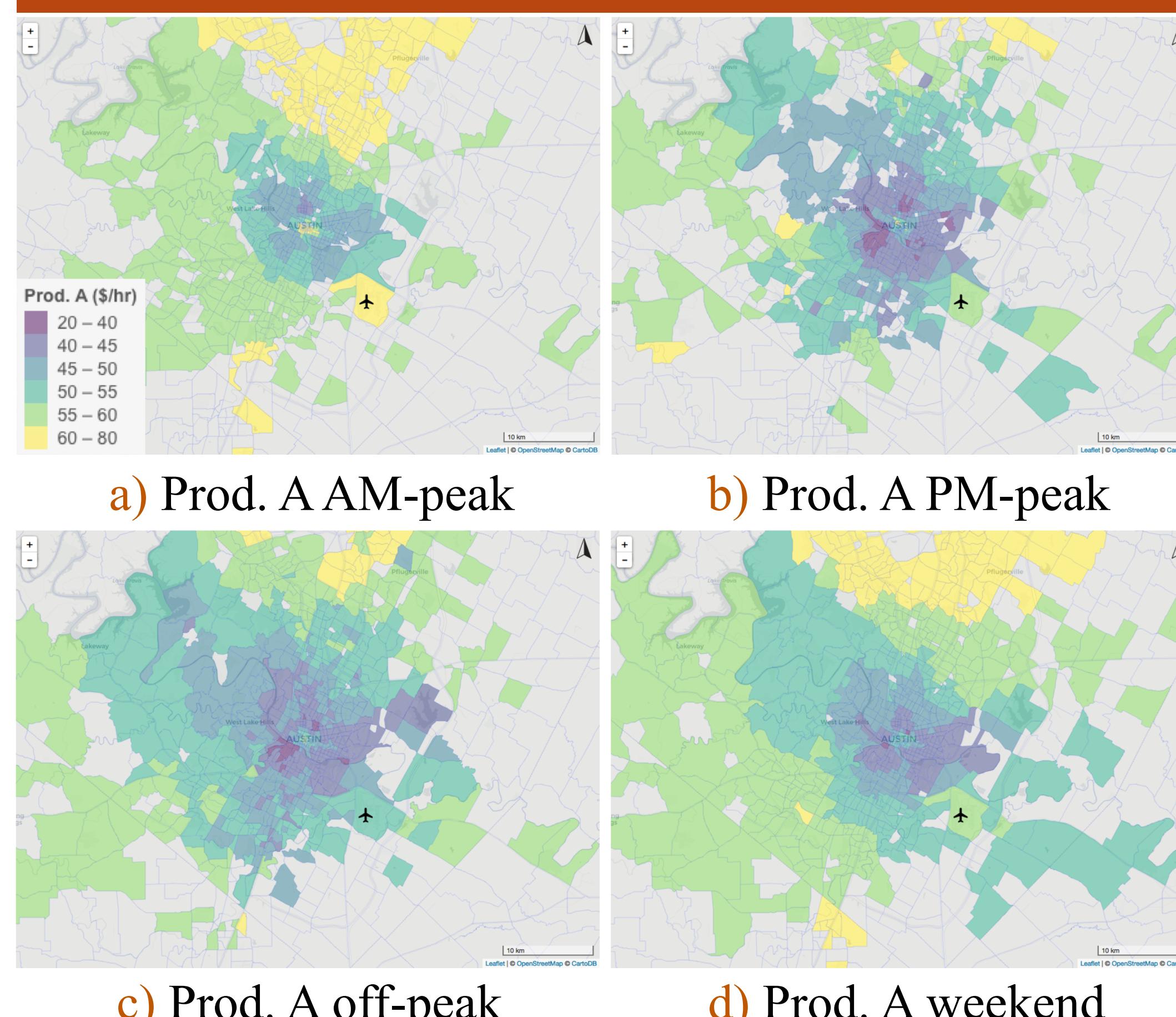
One way to estimate x is by using the GFL, defined by a convex optimization problem that penalizes the first differences of the signal across edges.

$$\min_{x \in \mathbb{R}^n} \sum_{i=1}^n \frac{\eta_i}{2} (y_i - x_i)^2 + \lambda \sum_{(r,s) \in \mathcal{E}} |x_r - x_s|$$

Where, r is the start node and s is the end node, η_i is the count of trips observed within the i -th TAZ, and $\lambda > 0$ is the regularization parameter.



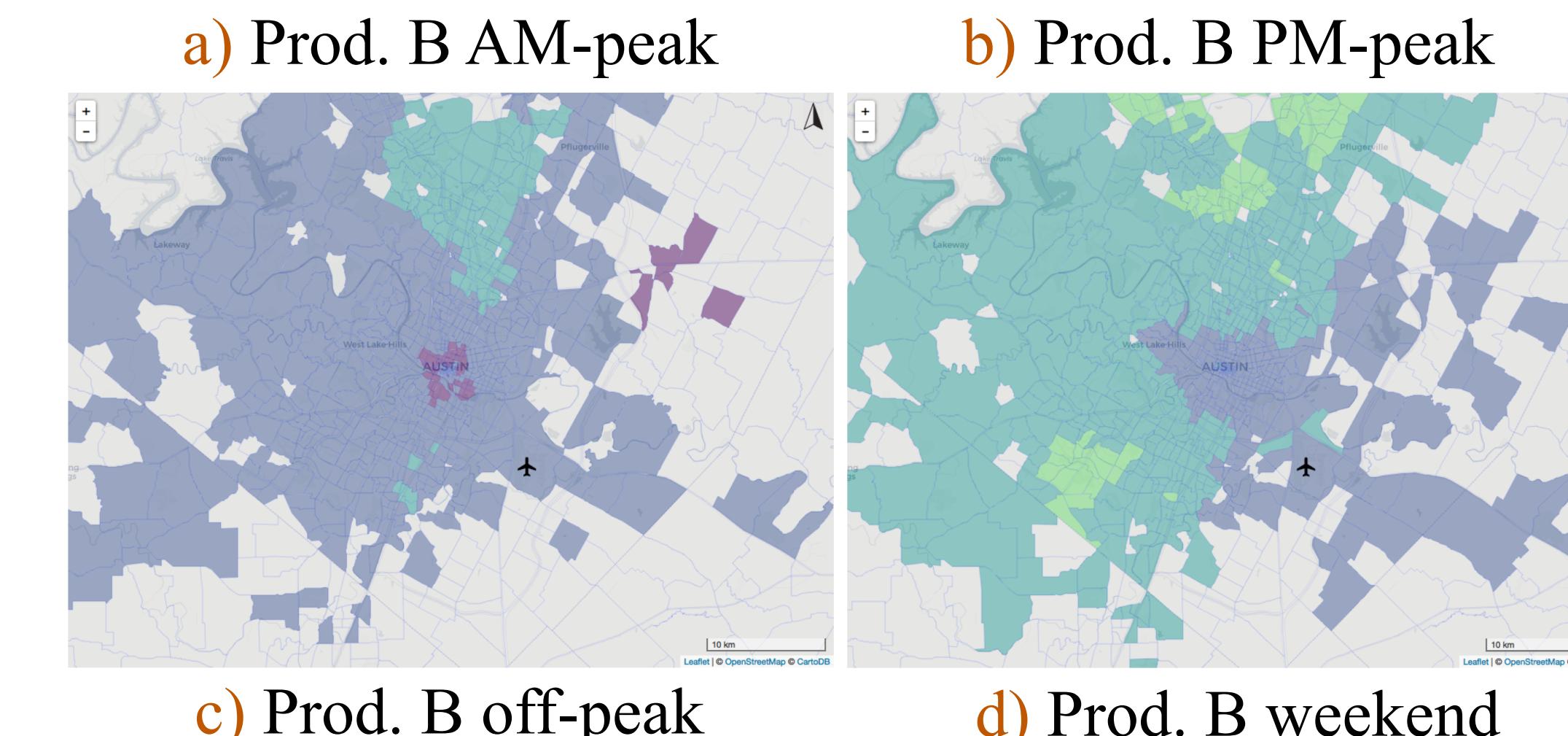
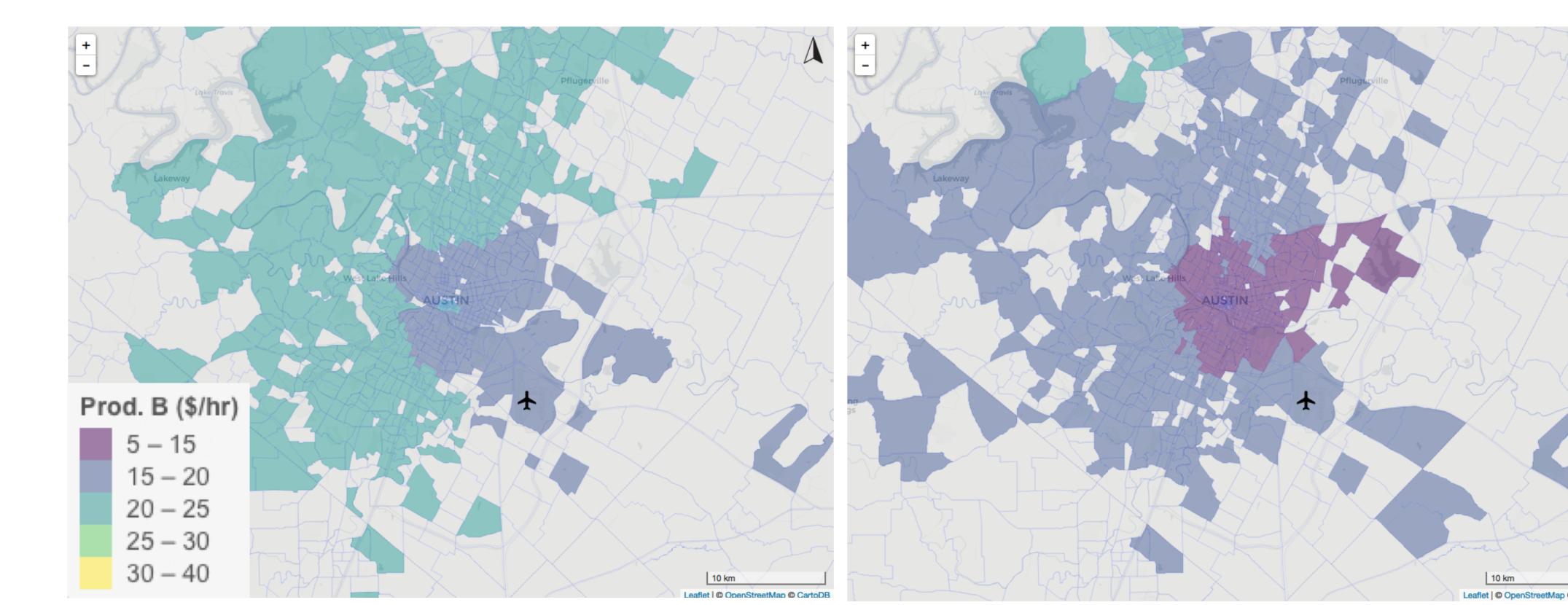
Results



Productivity A

- Driver productivity for a single journey
- Donut-like effect
- Comparable between trips of fewer than 0.8 kilometers and longer than twenty-five kilometers

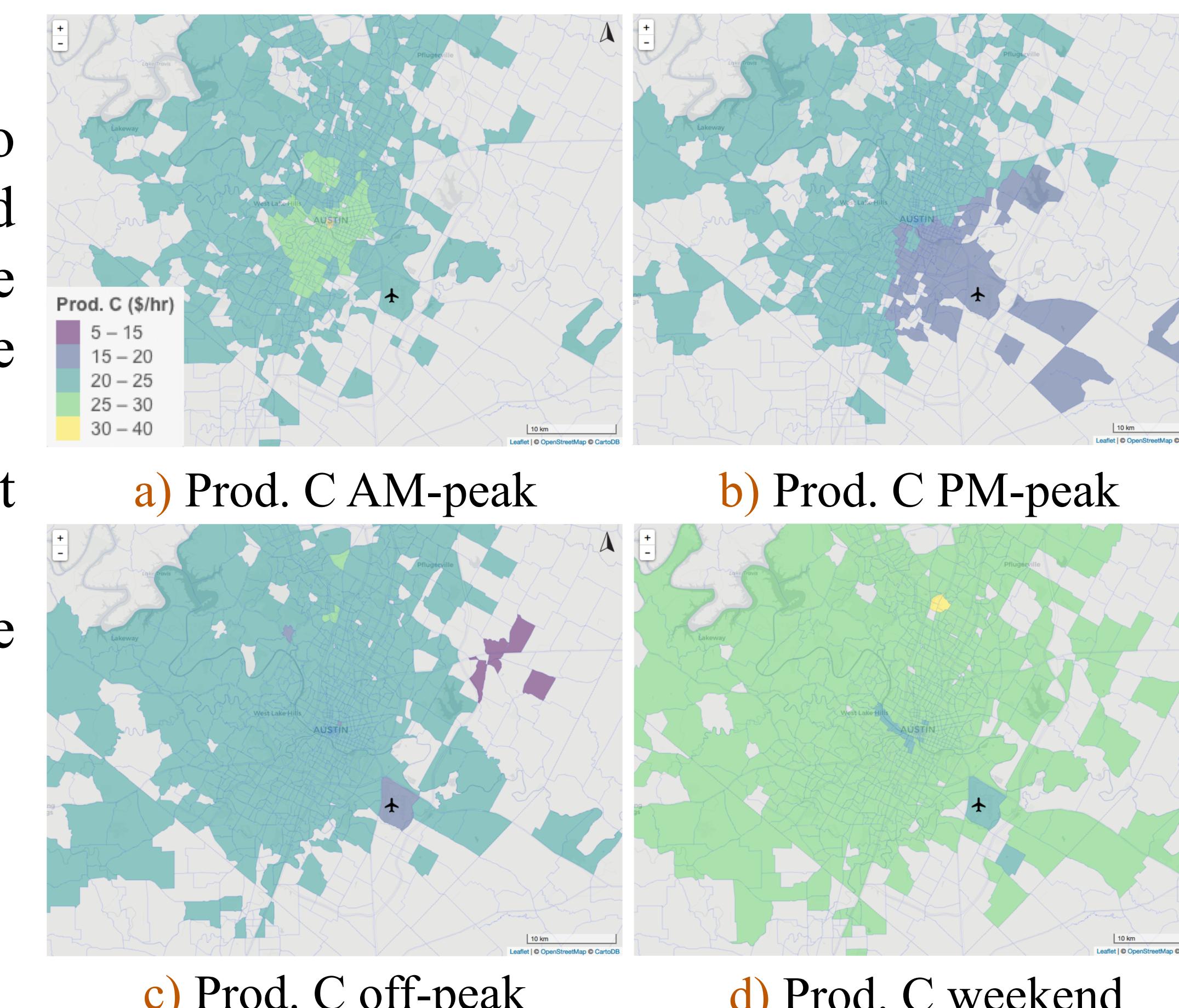
$$Prod. A = \frac{fare_{trip1}}{t_1}$$



Productivity C

- Productivity of two consecutive trips and takes into account the ending-zone idle time between them
- Lower spatial impact compared to Prod. B
- Weekend trips are more favorable for drivers

$$Prod. C = \frac{fare_{trip1} + fare_{trip2}}{t_4}$$



Conclusions

Primary findings of this research suggest that there are differences in space and time that can affect ride-sourcing search frictions and driver productivity. Providing spatio-temporal pricing strategies could be one way to balance driver equity across the network.

- Driver and operator point of view**
More efficient driver supply method.
- Planners and engineer's perspective**
Understand the characteristics of the ride-sourcing service in Austin.
- Pricing strategies and policies**
Warranty fair conditions in driver compensation.