Universität St.Gallen
Institut für Mobilität

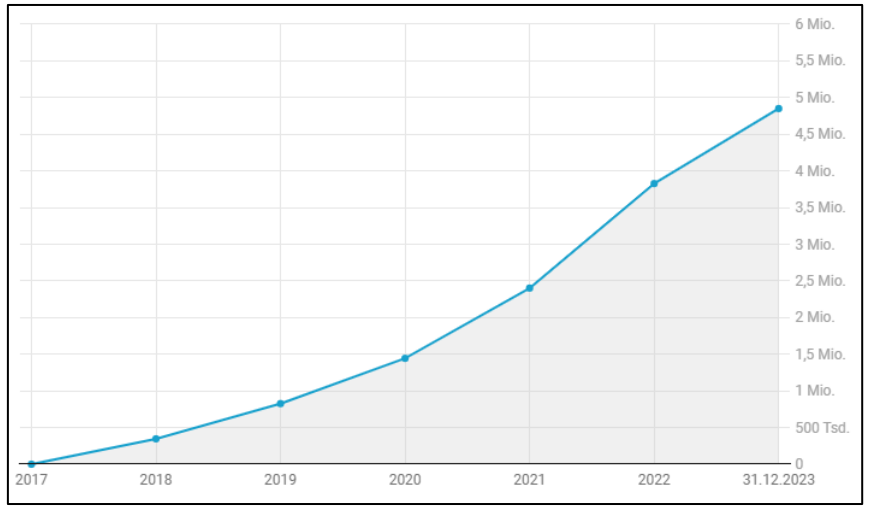
How many is optimal? The relationship between shared e-scooter density and usage

TRS 2025, Rotterdam

Matthias Brüning, University of St.Gallen
Aoyong Li, Beihang University
Konstantin Krauss, ETH Zürich (alumni)

The life and death of shared e-scooters…

E-Scooter trips in Switzerland



(CHACOMO, 2024)

Madrid moves to ban app-rented e-scooters over safety concerns

Lime, Dott and Tier Mobility licences to be cancelled from October due to issues with circulation and parking



E-scooter operators were 'incapable' of meeting safet
Photograph: Violeta Santos Moura/Reuters

Paris says au revoir to rental e-scooters

1 September 2023

Share Save

Hugh Schofield
BBC News, Paris



Shared e-scooters require efficient regulation to balance city burden and utility







How many is too many?...

...But how many is not enough?

The literature suggests a strong relationship between fleet density and usage, but a "plateau effect" when observing a high density

Higher density leads to higher use



"When the number of e-scooters available for any given operator **was capped** […] a **drop in demand** [was observed]." (Aarhaug et al., 2023)

…until a "plateau effect" reached



"A "**plateau effect**" is observed with decreasing marginal utility gains for increasing fleet densities." (Reck et al., 2021)

- **No integrated study** to guide regulators towards an **optimal limit**

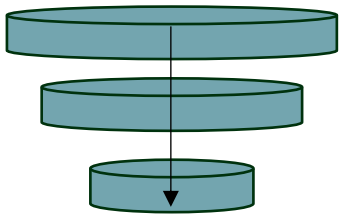
"What is the nature of the non-linear relationship between shared e-scooter fleet size, availability, and usage?"

Data: The model is developed using data from 90 German cities with shared e-scooters

Raw data set & processing

Largest data set of full market data (**all providers** within one city) for shared e-scooter availability and use (90 cities in Germany)

- Locations of all scooters at time x (every 2-10 min.) with identifiable ids
- Weather



Raw data

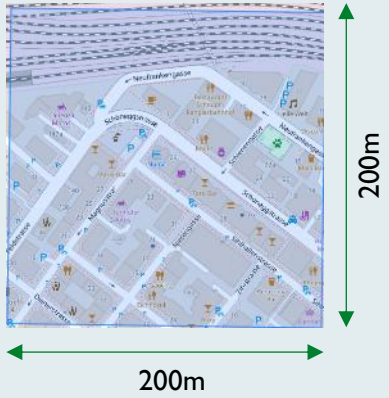
Calculated trips (ID tracking)

Cleaned trips (e.g. routing and speed matching)

Geometrical aggregation

Splitting each city into 200m squares, adding covariates to infer demand patterns

- Inhabitants
- Street length
- POIs (e.g. train station, # restaurants)
- Centrality

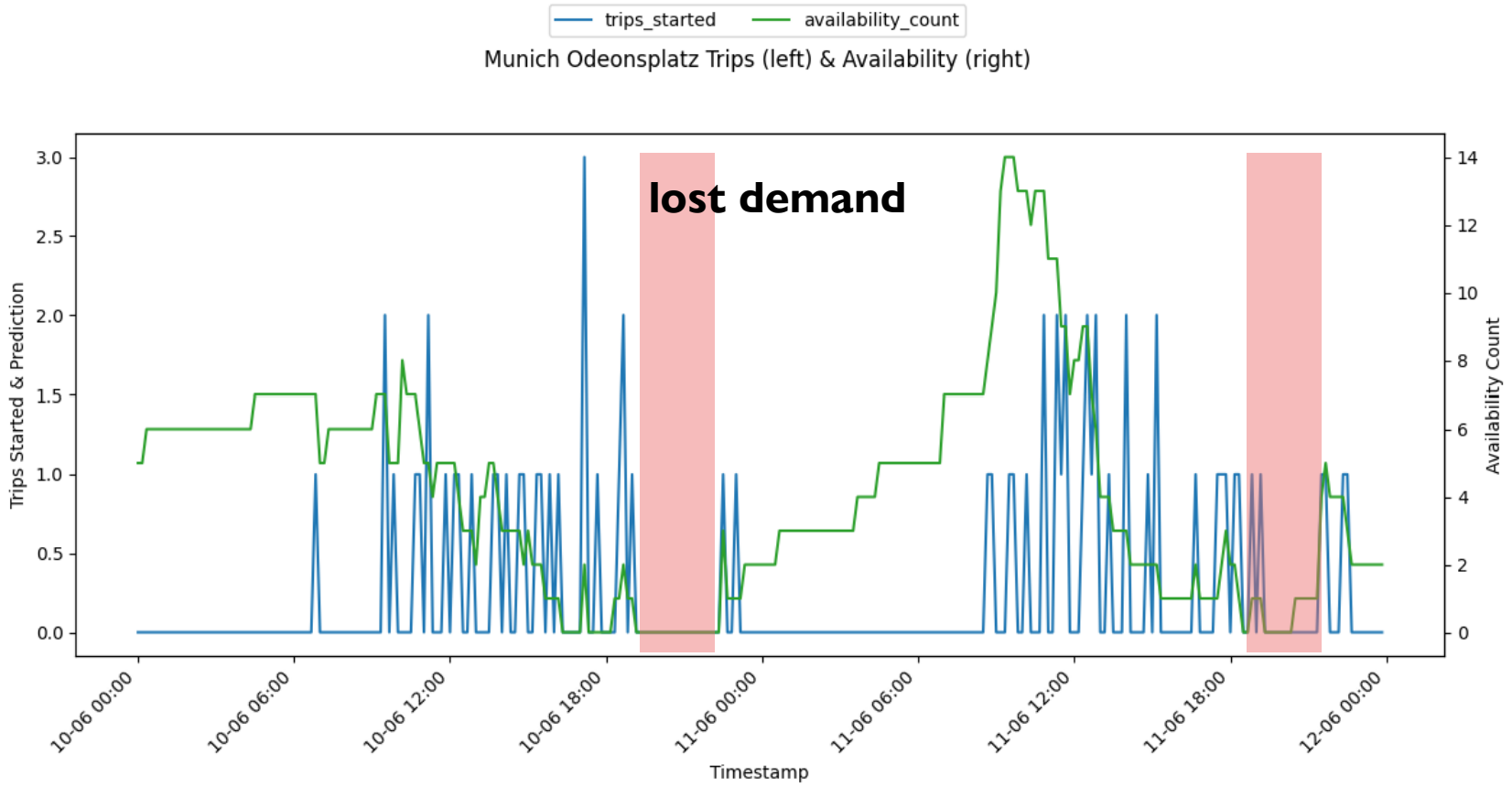


≈ 80,000 squares within service area
(> 20th percentile of trips)
≈ 220,000,000 time series data points (3 weeks)

We see scooter crowds because demand is highly cyclic



Example Munich Odeonsplatz
About 44 rides / day



To account for different environments, we are estimating separate models for city centers, urban areas and suburbs

Center

Avoid congestion



1.5th percentile closest to center

Urban

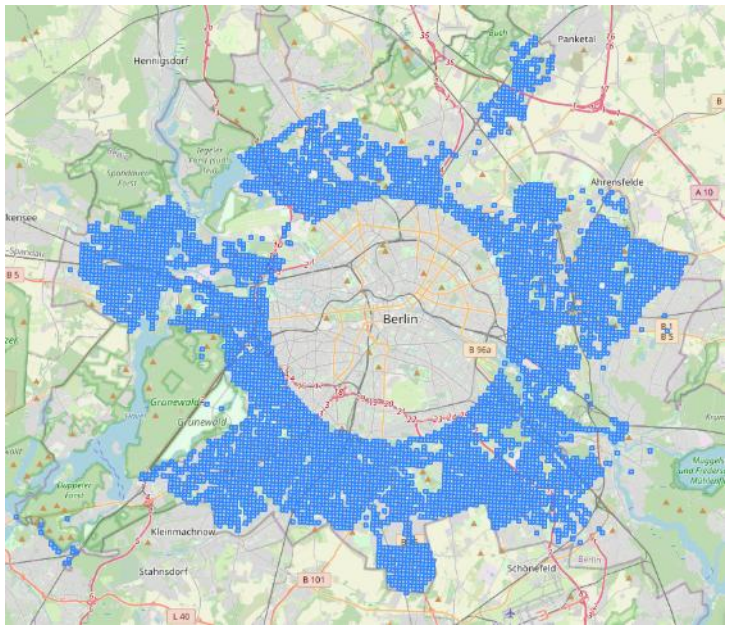
Balance availability & congestion



15th percentile closest to center

Suburban

Ensure availability



>15th percentile closest to center

Two approaches for dealing with endogeneity

Density —endogenous→ **Usage**

Operators place more vehicles in areas of high demand

Approach 1: Censored demand model

1. Predict latent demand for each square given sufficient availability
2. Model relationship between lost demand and fleet size

- Supply only enters the model as limiting factor, not potential demand driver

Used for **center** and **urban** model

Approach 2: Local predictions with aggregated fleet sizes

Predict trips for each square using aggregated fleet size (average scooter/square) as feature

- Aggregated fleet size has a strong political component (set by city authorities)
- Model trains on proxy for general availability, not strongly endogenous local availability

Used for **suburban** model

In the first stage, lost demand is predicted with a neural network

Fit a **neural network** with a **custom loss function**

Target: **Trips started** within 10 minutes in 200m square
Features: Grid characteristics, time variables, weather, average demand

Loss function

$$L_i = w_i^{\text{unc}}\, \ell_{\text{base}}(\hat{D}_i, Y_i) + w_i^{\text{cens}}\, \ell_{\text{cpen}}\big(\max(0,\, Y_i - \hat{D}_i)\big)$$

Base loss
(= regular Poisson loss)

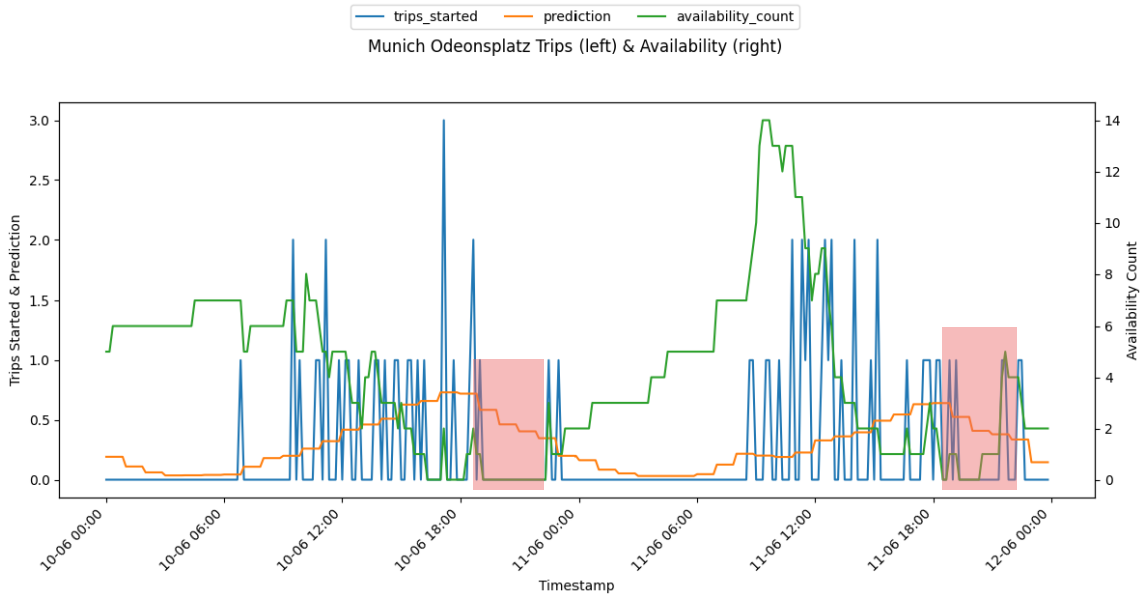
Censorship probability

Penalty for underpredicting censored observations

Censorship probability based on **sigmoid function**

$$w_i^{\text{unc}} = \sigma\big(k\,(g_i - \text{offset})\big) = \frac{1}{1 + \exp\big(-k\,(A_i - Y_i - \text{offset})\big)}$$

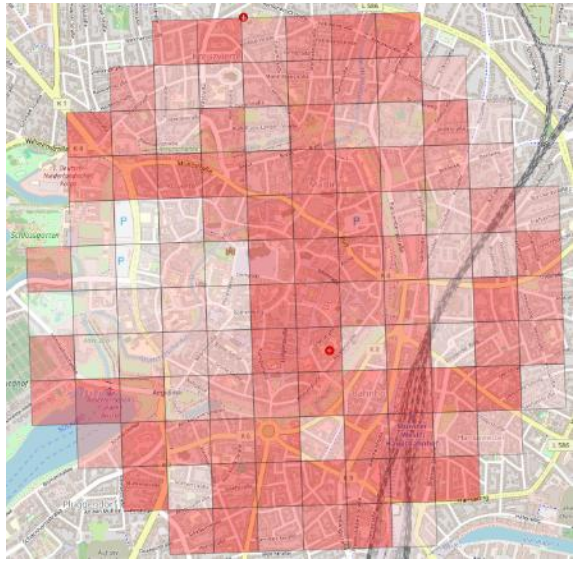
Predicted lost trips



Depending on the fleet density we see differences in lost trips

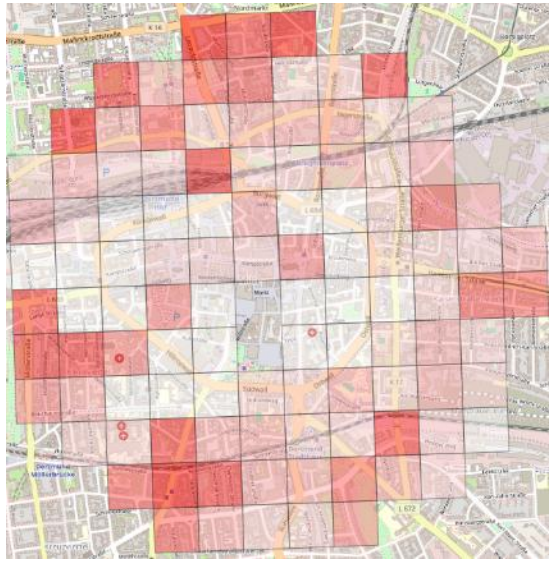
Münster

Avg. density: 3.3 scooters



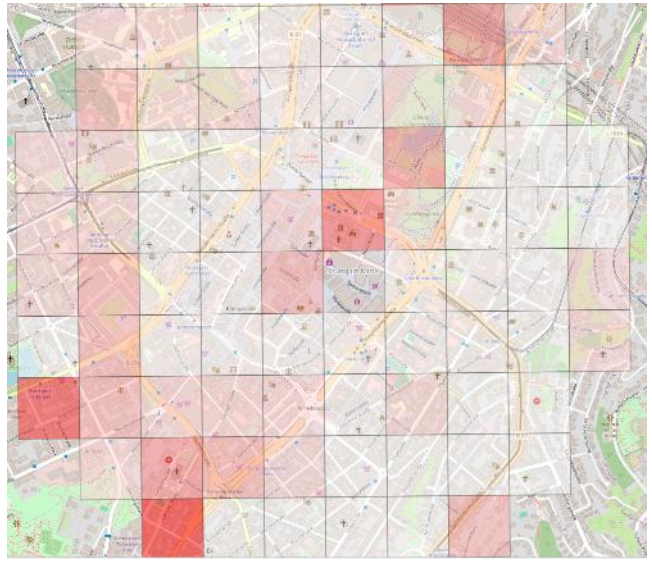
Dortmund

Avg. density: 5.8 scooters



Stuttgart

Avg. density: 10.4 scooters



Lost demand

high medium low

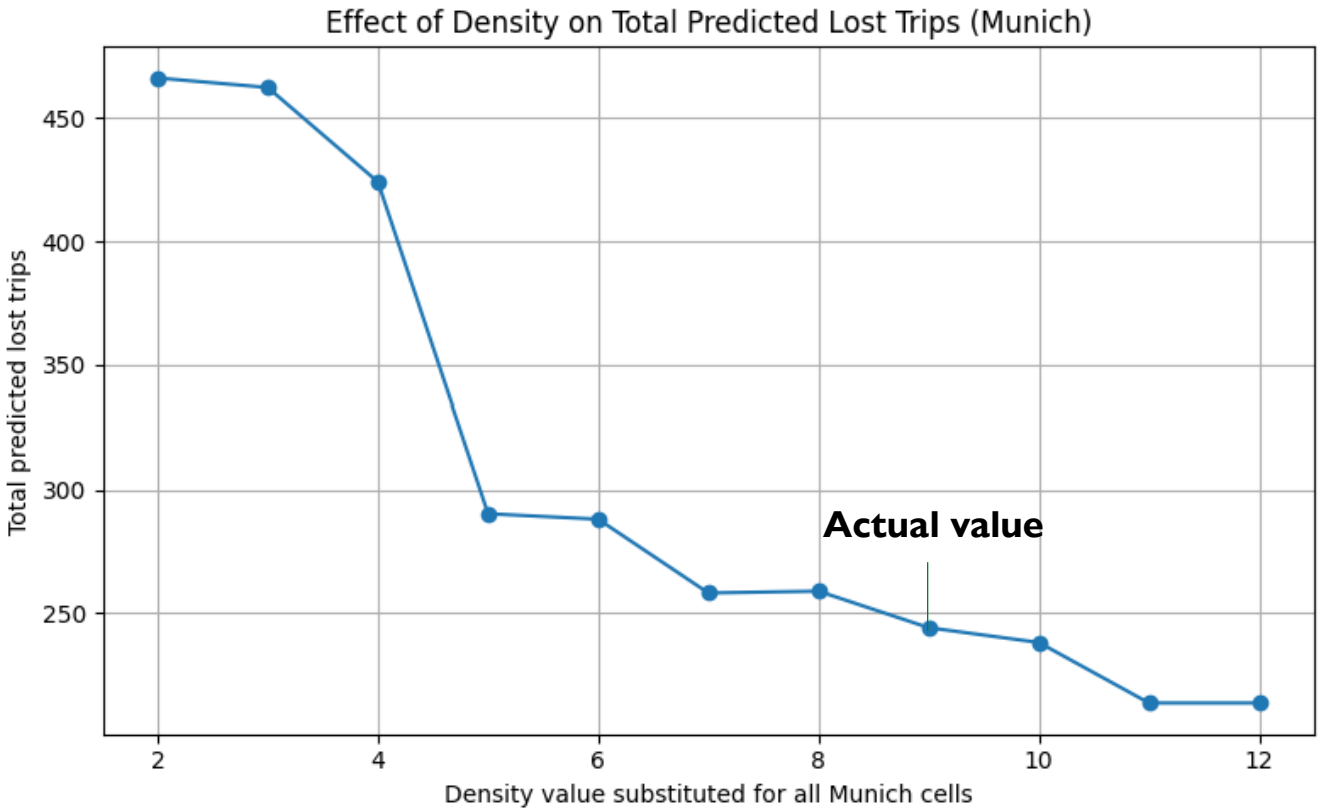
In the second stage, we predict the influence of fleet size on total lost demand

Fit a **gradient booster**

Target: **Lost trips** (sum of 3 test days) within 200m square

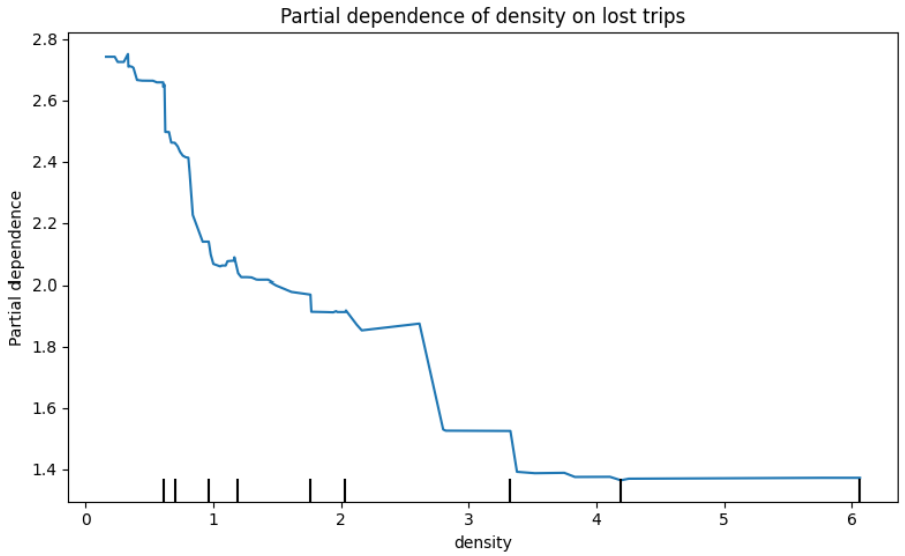
Features: **Aggregated average density** (scooter / square), grid characteristics, average demand, city

Predictions for Munich center

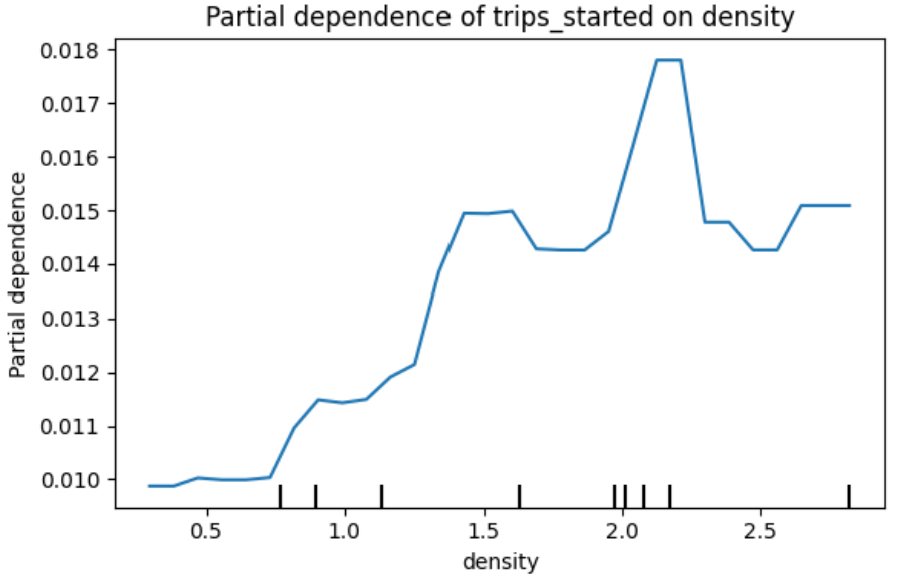


Further results indicate similar patterns in urban / suburban areas

Urban setting (lost trips)

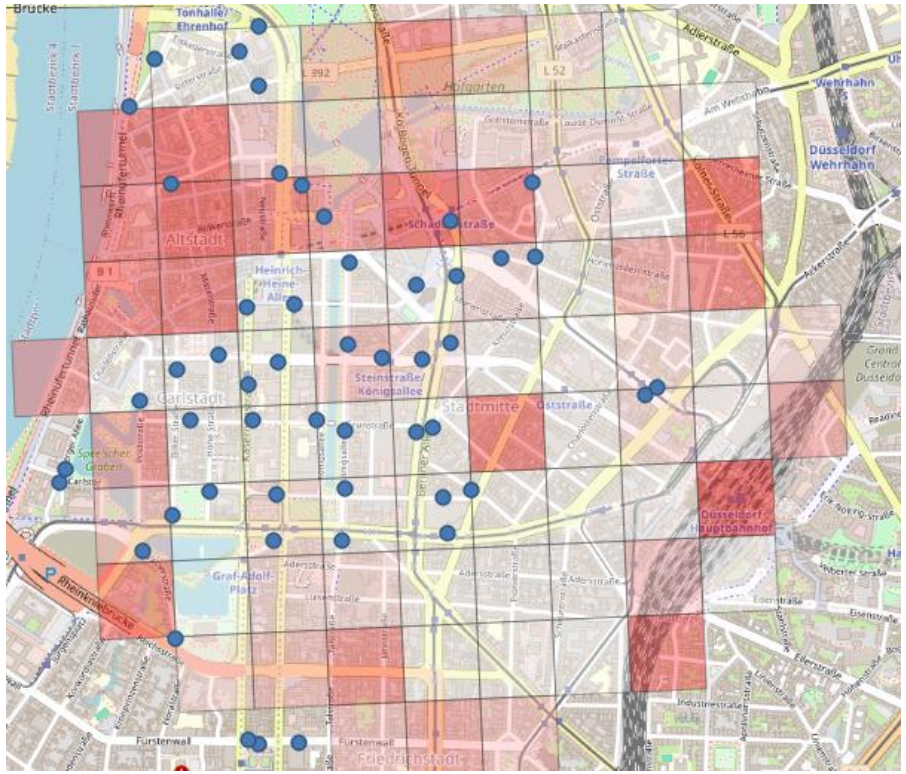


Suburban setting (trips started)



Sharing zones seem to increase availability and prevent lost trips

Example Düsseldorf



Controlling for demand factors, there is a statistically **significant negative association** between presence of a sharing zone and predicted lost trips, as well as availability > 0 within a 200m square

First conclusions call for a differentiated policy

- Setting an efficient fleet size is highly challenging due to **cyclic demand patterns. There is no single optimal value.**
- Learned relationships within the models indicate there might be **diminishing returns** at an average of 5-6 scooters / 200m square within centers, 3-4 scooters in urban areas and 2 scooters in suburban areas.
- Predictions further indicate a **minimum** of 1.5 scooters before significant gains are achieved.
- **Sharing zones** might help to reduce availability problems.

Limitations & next steps



- Results are **associations** based on **predictions**, not causal relationships. Endogeneity concerns have been reduced but persist.

  → Leverage data from active policy changes (e.g. Oslo)

- Latent demand censorship model dependent on **manually** defined sigmoid curve and not capturing full latent demand.

  → Explore learning censorship from the data

- Current model is **provider agnostic**.

  → Explore the influence of provider count

Thank you!

Feedback? Interested in the data set?
Let‘s connect!