What determines the spatial patterns of Airbnb rentals in Chicago?

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Airbnb

- The rise of the sharing economy is having far reaching consequences in a variety of sectors
- Two of the biggest names are Uber and Airbnb
- Launched in 2008, Airbnb provided an online platform which radically simplified the process of arranging a short-term rental
- This gave consumers new accommodation options and property owners a new source of income

In the beginning

- The idea was that people could rent out a sofa or a spare room
- This would generate extra income for hosts and give cheap accommodation to guests
- There was a strong social aspect which would allow guests to meet a resident of the city they were visiting
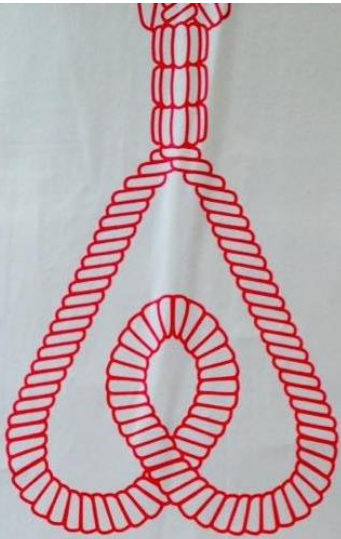
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Since then

- The platform became increasingly professional, with people renting out entire homes
- Some landlords have several properties which they rent out on Airbnb
- Companies have appeared to help hosts manage advertising, customer service, cleaning and so on

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Who pays for your holiday?

When you book an apartment, think about the rising rent prices for locals, an increase in touristification and people going through social displacement. For each holiday apartment a local tenant has to leave their home.

#boycottairbnb

Castrate gentrification.

When you book an apartment, think about the rising rent prices for locals, an increase in touristification and people going through social displacement. For each holiday apartment a local tenant has to leave their home.

#boycottairbnb

Stop milking it.

When you book an apartment, think about the rising rent prices for locals, an increase in touristification and people going through social displacement. For each holiday apartment a local tenant has to leave their home.

INTERDIT ICI!

airbnb

FORBIDDEN HERE!

airbnb

LIES

NEIGHBORHOODS ARE
FOR NEIGHBORS
NOT VACATION RENTALS!

BIRCH THE PLAZA
RESIDENTS SAY NO TO HOMESTAY
AND SHORT STAY
民宿不受欢迎

- Gentrification
- Crowding out residents / pushing up rents
- Tax evasion
- Regulatory non-compliance
- Anti-social behavior
- Anticompetitive practices
- Racism
- Sexism
- Zionism
- Anti-Semitism

Policy

- Policy makers are left not knowing what to do and not having much evidence
- A variety of regulatory regimes are in place around the world
- These are enforced to differing extents
- In many places it is a legal grey area

Data

- Airbnb do not supply data, but publish their own analysis
- Companies such as AirDNA scrape data from Airbnb's website, augment it, and sell it on
- Inside Airbnb also scrapes the Airbnb website and makes it available free of charge

Our preliminary work

- We have been playing with Airbnb data from Chicago
- We have used various regression models to explain

  1. What explains the distribution of rentals?
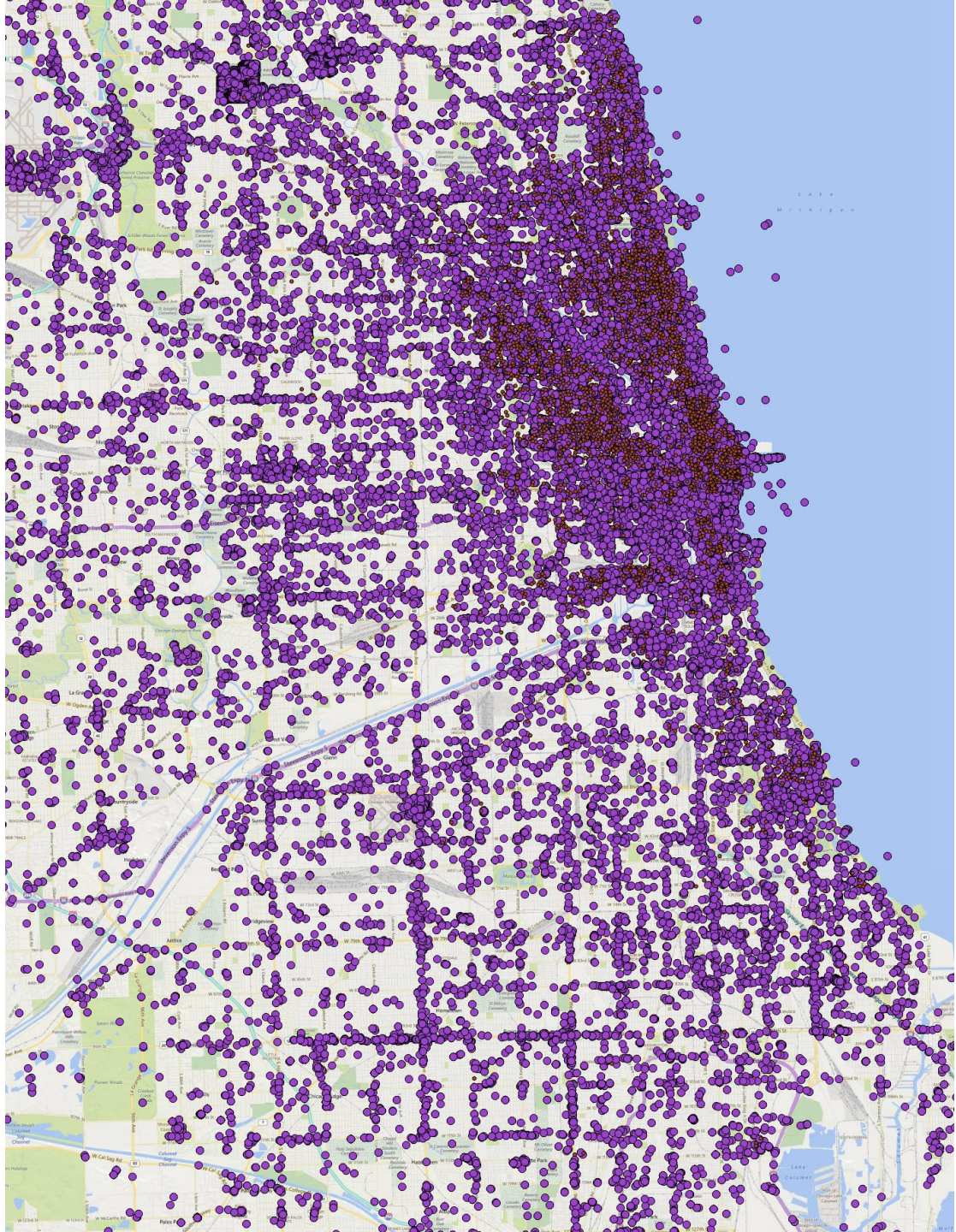
  2. What explains variation in price
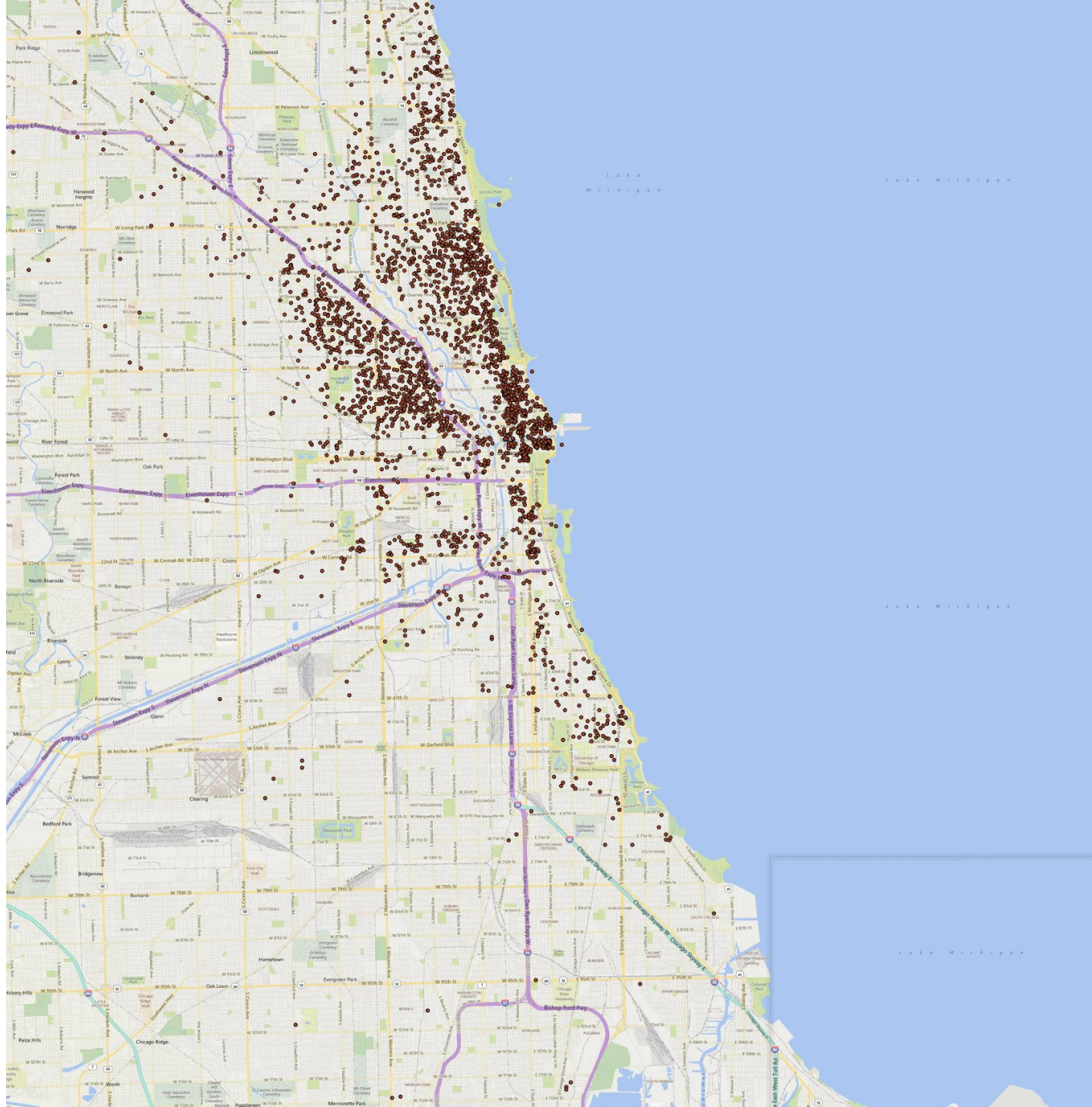
Location

- Guests like to be close to amenities
- One approach to measuring the presence of urban amenities is to measure the distance to the city centre
- This doesn't seem to make sense for Chicago
- We want another measure of the density of urban amenities

Twitter

- Some people like to tweet to show off being in an interesting location
- We gathered all geotagged tweets from Chicago over a period of several months

Problems

- Interpreting the number of tweets as a measure of amenities is problematic

Kedzie Ave

Sherman Ave

Custer Ave

Madison St

Madison St

Madison St

Sherman Ave

Custer Ave

Chicago Ave

Monroe St

Monroe St

Monroe St

Custer Ave

JD Mill

ve

Chicago Ave

Sherman Ave

Reba Park

Custer Ave

Reba Pl

Reba Pl

Reba Pl

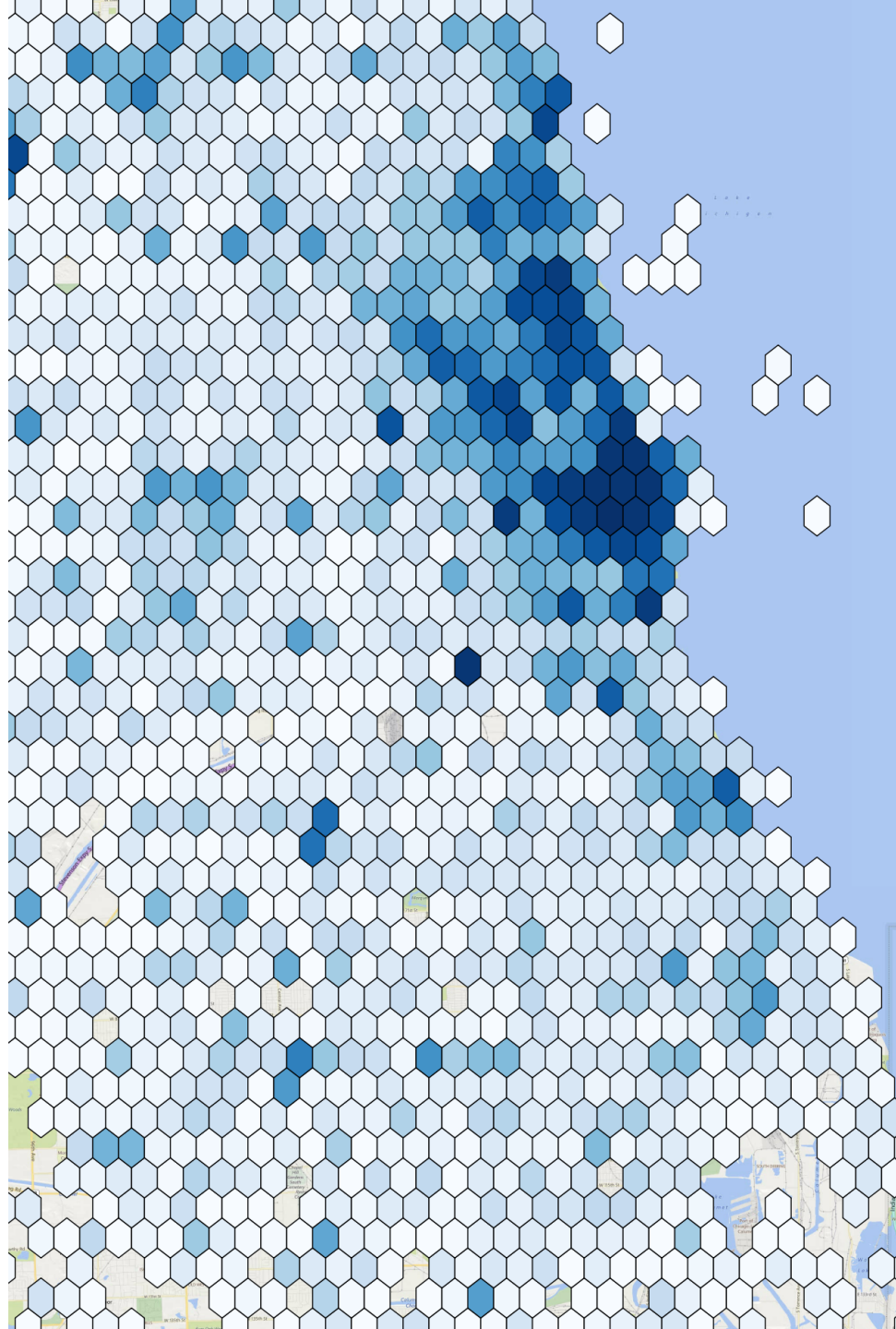Reba Pl

Reba Pl

Sherman Ave
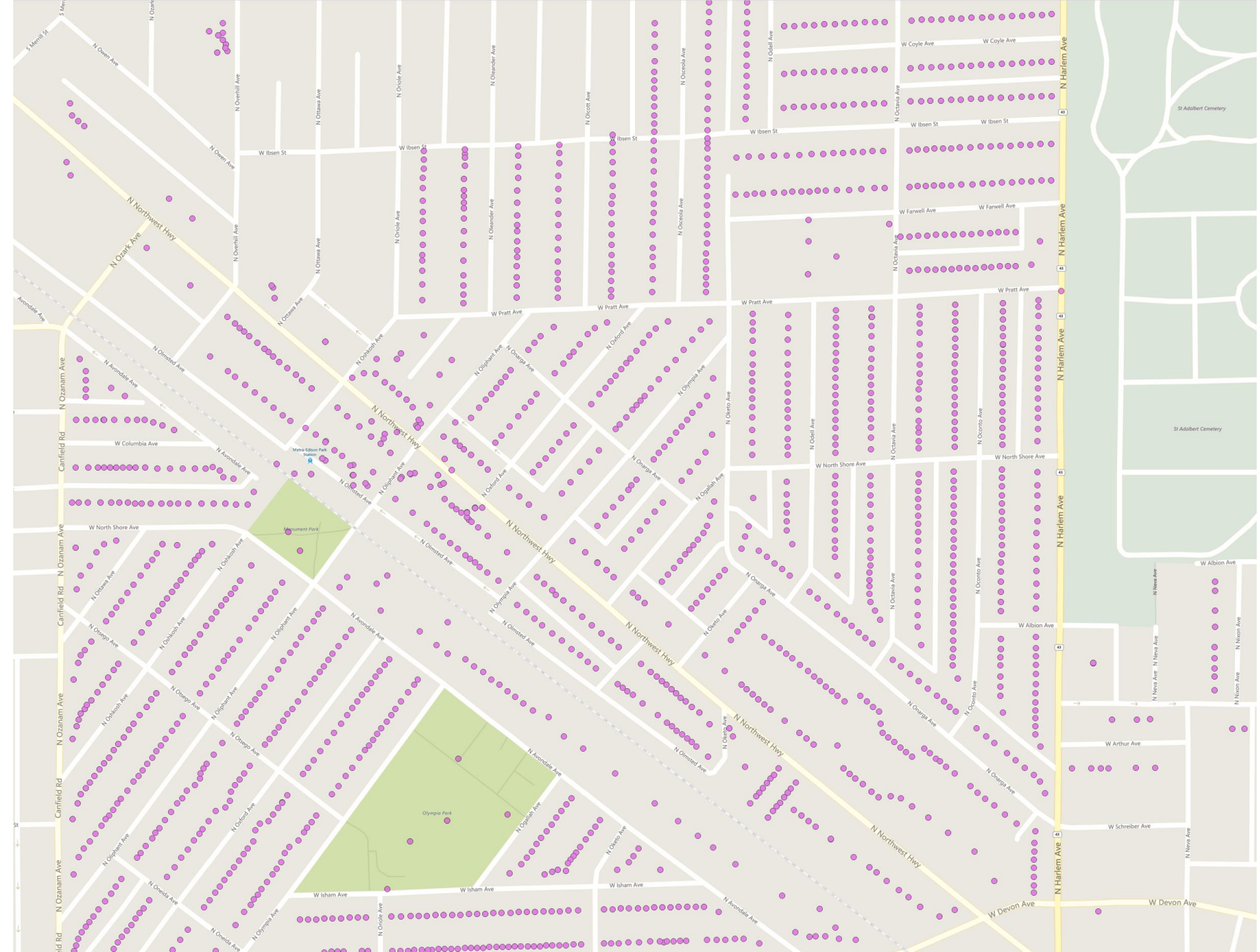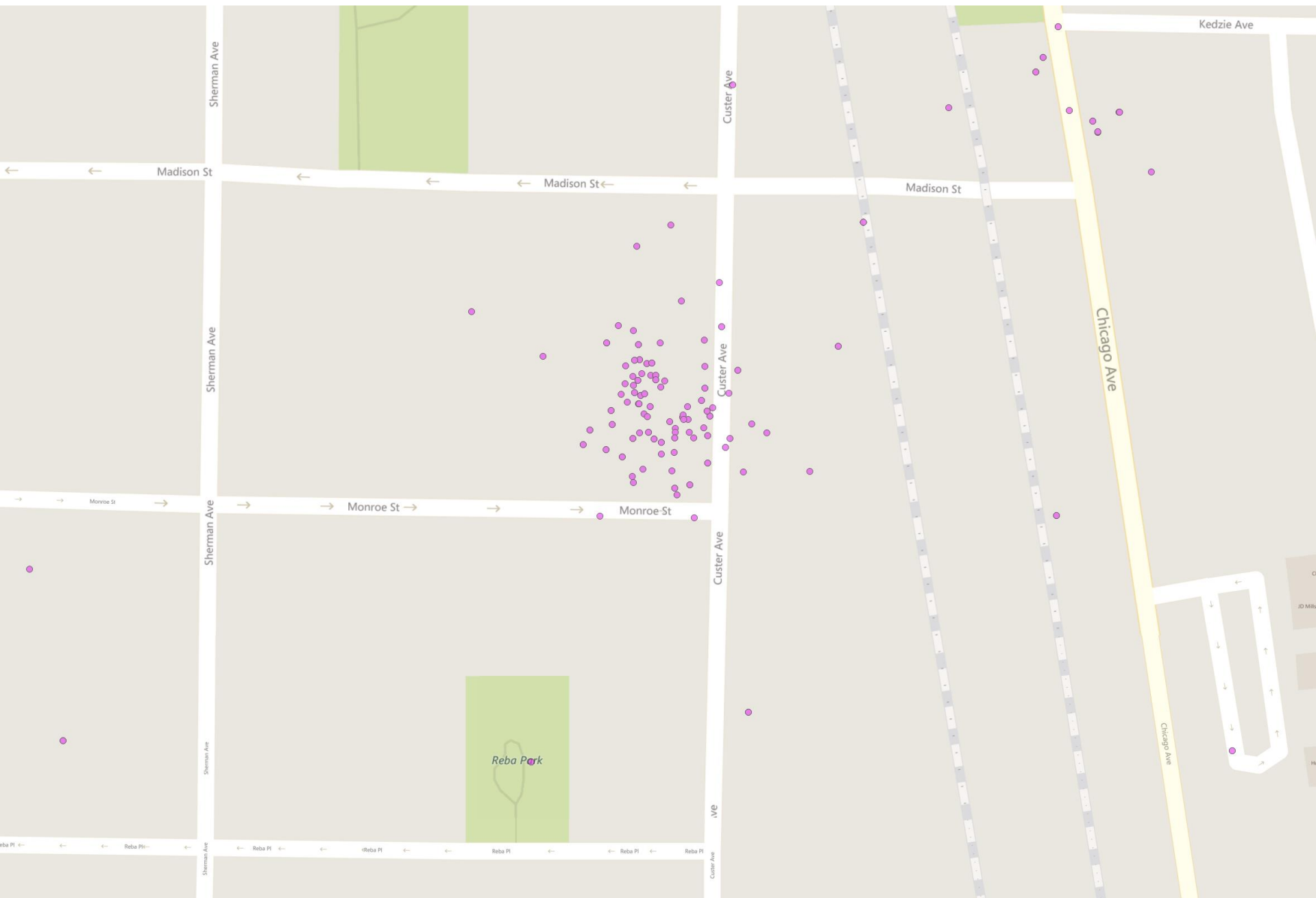
Potential Solutions

- Number of unique users in an area
- The entropy of the tweets in an area

$$S = -\Sigma_i P_i \log_2 P_i$$

$$P_i = \frac{tweets_i}{\Sigma_i tweets_i}$$

- Quantifies the uncertainty involved in assigning a randomly selected tweet to a user

- Takes a maximum value of $\log_2 n$
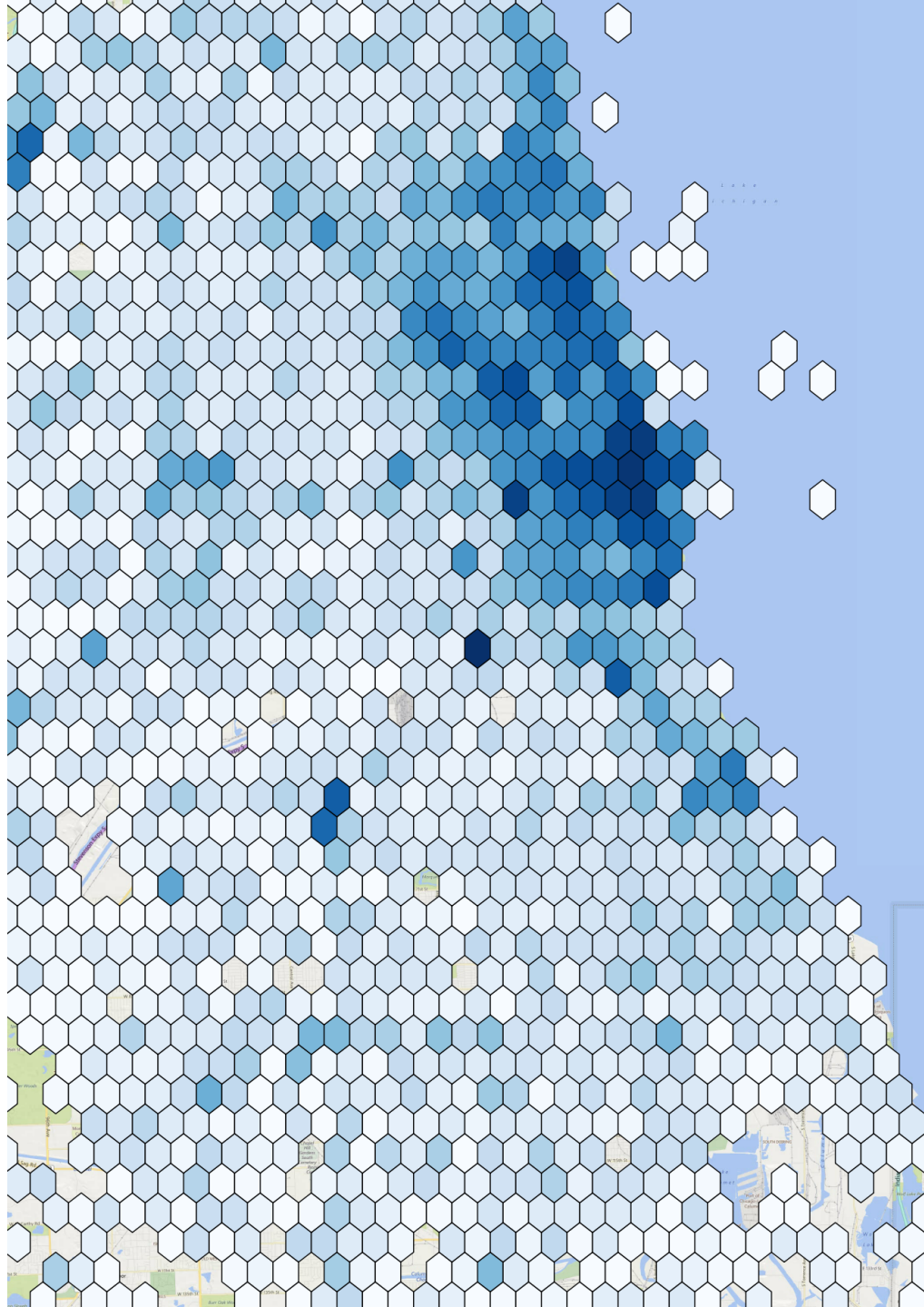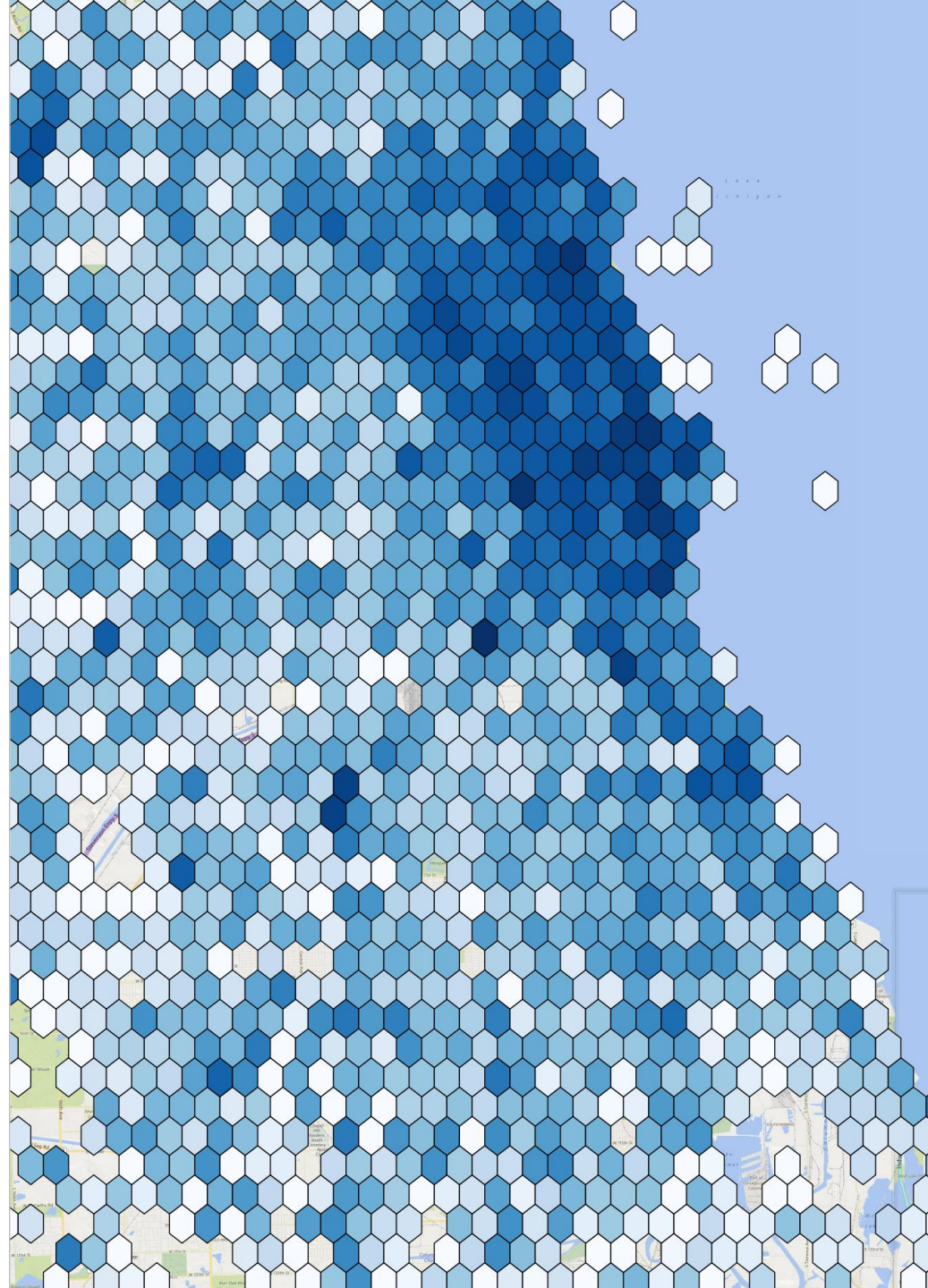
Modelling

- We estimated several econometric models to look at the density of Airbnb rentals and the price
- We found that a spatially weighted average of the entropy of tweets gave the best fit in the model
- We also show that the use of the twitter data improves the model specification

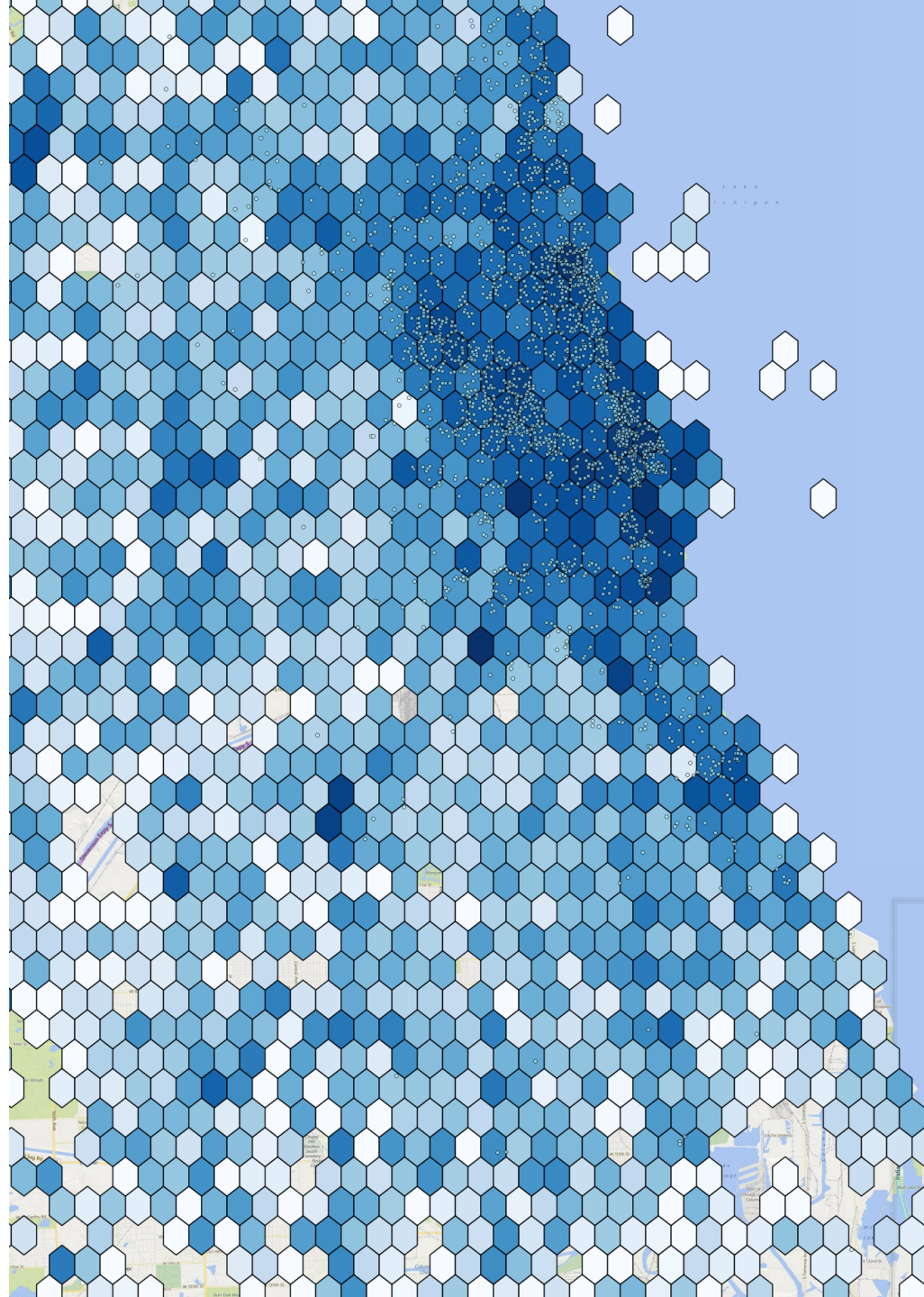|	Model 1	Model 2	Model 3	Model 4	Model 5
(Intercept)	4.5355***	4.8262***	4.4457***	4.3763***	4.0494***
	(0.0575)	(0.0573)	(0.0560)	(0.0547)	(0.0556)
Accommodates	0.0523***	0.0435***	0.0468***	0.0451***	0.0432***
	(0.0051)	(0.0048)	(0.0049)	(0.0048)	(0.0046)
One bedroom	0.1225***	0.1619***	0.1585***	0.1736***	0.1765***
	(0.0284)	(0.0268)	(0.0275)	(0.0268)	(0.0257)
Two bedrooms	0.1958***	0.2880***	0.2658***	0.3026***	0.3141***
	(0.0315)	(0.0301)	(0.0309)	(0.0301)	(0.0288)
Three bedrooms	0.2309***	0.4070***	0.3585***	0.4194***	0.4387***
	(0.0404)	(0.0393)	(0.0401)	(0.0392)	(0.0374)
For or more bedrooms	0.3451***	0.5845***	0.5104***	0.5833***	0.6029***
	(0.0614)	(0.0594)	(0.0605)	(0.0590)	(0.0564)
Two bathrooms	0.3131***	0.2374***	0.2570***	0.2308***	0.2201***
	(0.0221)	(0.0212)	(0.0217)	(0.0212)	(0.0203)
Three or more bathrooms	0.5975***	0.5191***	0.5558***	0.5306***	0.5096***
	(0.0515)	(0.0488)	(0.0498)	(0.0485)	(0.0466)
Wireless	0.2222***	0.1722***	0.1915***	0.1767***	0.1675***
	(0.0499)	(0.0471)	(0.0483)	(0.0469)	(0.0451)
Medium cancellation	-0.0570**	-0.0430*	-0.0519**	-0.0494**	-0.0308
	(0.0179)	(0.0169)	(0.0173)	(0.0168)	(0.0162)
Difficult to cancel	-0.1702***	-0.1535***	-0.1575***	-0.1543***	-0.1498***
	(0.0226)	(0.0213)	(0.0219)	(0.0213)	(0.0204)
Host time on platform	0.0264***	0.0249***	0.0297***	0.0296***	0.0208***
	(0.0048)	(0.0045)	(0.0046)	(0.0045)	(0.0043)
Extra fee	-0.1216***	-0.0870***	-0.0956***	-0.0781***	-0.0675***
	(0.0170)	(0.0162)	(0.0166)	(0.0162)	(0.0155)
Highly rated	0.1101***	0.1110***	0.1146***	0.1107***	0.1007***
	(0.0170)	(0.0160)	(0.0164)	(0.0159)	(0.0153)
Distance to CBD		-0.0636***			
		(0.0056)			
Distance to CBD squared		0.0019***			
		(0.0004)			
Tweets			0.0115***		
			(0.0008)		
Twitter users				0.0974***	
				(0.0052)	
Twitter entropy squared					0.0025***
					(0.0001)

R^2	0.4238	0.4881	0.4620	0.4916	0.5308
Adj. R^2	0.4210	0.4852	0.4592	0.4890	0.5284
Num. obs.	2676	2676	2676	2676	2676
ℓ	-1344.991	-1186.654	-1253.324	-1177.467	-1070.121
RESET	0.07	0.65	7.21***	5.179***	1.60
Breusch-Pagan	32.41***	22.06	48.86***	34.55***	19.95
Mean VIF	1.68	1.68	3.03	1.66	1.65
RMSE	0.4010	0.3781	0.3876	0.3768	0.3620
Moran's I	0.24***	0.17***	0.20***	0.17***	0.10***
LM Error	2506.85***	1345.51***	1856.99***	1237.57***	427.71***
LM Lag	1279.15***	568.29***	853.12***	565.29***	168.85***
RLM Error	1229.55***	777.46***	1004.15***	673.78***	259.26***
RLM Lag	1.85	0.25	0.28	1.50	0.40

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

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- Finish off our work on Chicago
- Compare Airbnb across 4 UK cities – are the patterns similar?
- Try to estimate the impact of Airbnb on prices and rents
- Does Airbnb affect the supply of rental accommodation?

Thank you for your attention

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