Equity & Micromobility

A statistical analysis of e-scooter and bike share in Chicago

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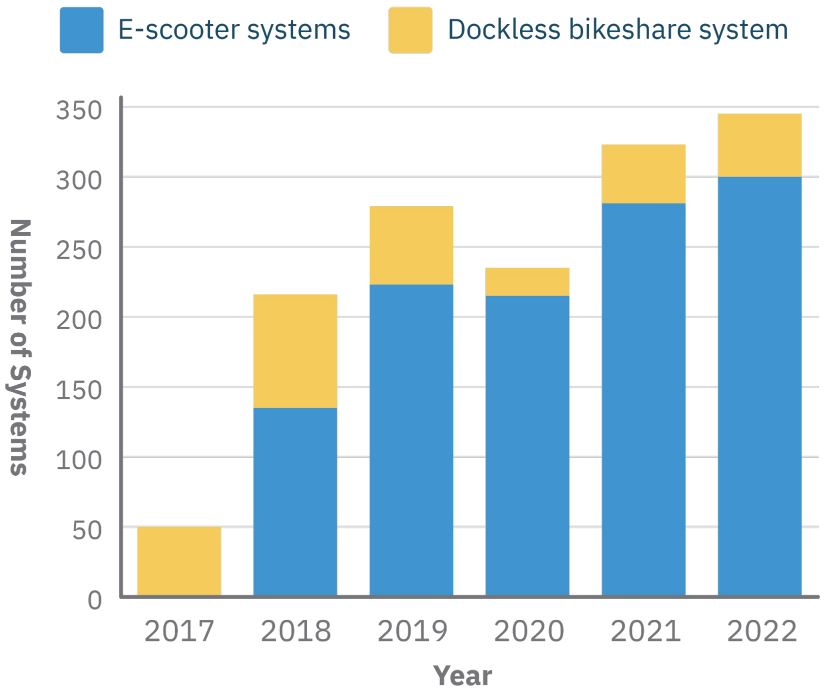
Micromobility is reshaping urban transportation

As public transit has struggled to recover ridership in the wake of the pandemic, micromobility systems have broken ridership records. Shared e-scooters were first deployed in Santa Monica in 2017, with fleets now in 158+ cities.

While the number of cities with e-scooter or bike share systems has decreased due to the volatility of private funding partners, they're growing rapidly in terms of stations, number of vehicles, and number of trips in the large cities which can sustain them.

Growth in dockless shared systems



Source: Bureau of Transportation Statistics

E-scooter and bike share in Chicago

We've chosen to focus our analysis on Chicago because of the composition of their bike and e-scooter share services. Divvy has grown rapidly, both in terms of number of trips and stations, since 2020. After e-scooter pilot projects in 2019 and 2020, Chicago launched permanent e-scooter sharing 2021. Chicago is the only city in the country which has both dockless e-scooters through private vendors and docked e-scooters through a city-operated system.

940,000

Divvy bike rides in July 2022, breaking the previous record set for rides per month in 2021

199

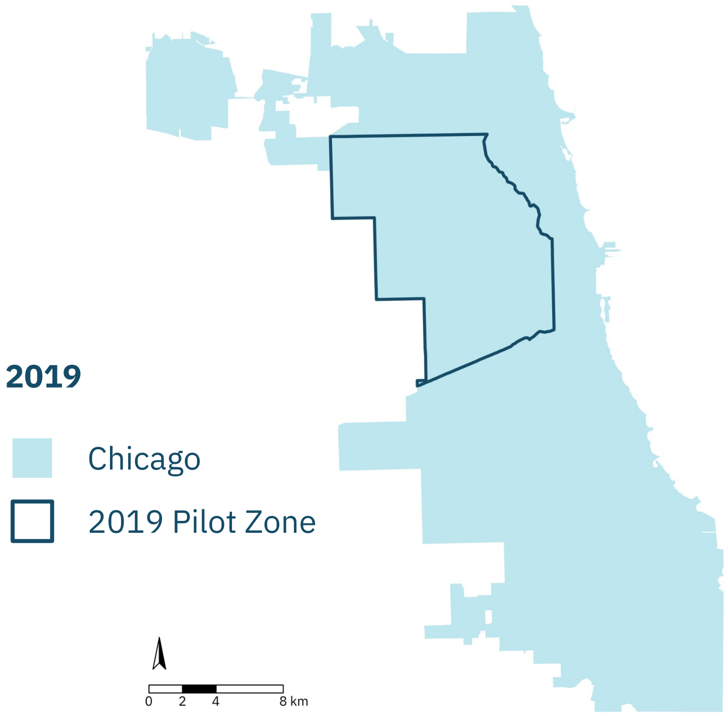
Stations installed since 2020—23% of the entire system

27%

Share of Divvy stations which introduced docked e-scooters in 2022

Sources: Block Club Chicago, Chicago Data Portal

Chicago's 2019 and 2020 E-Scooter Pilot Programs

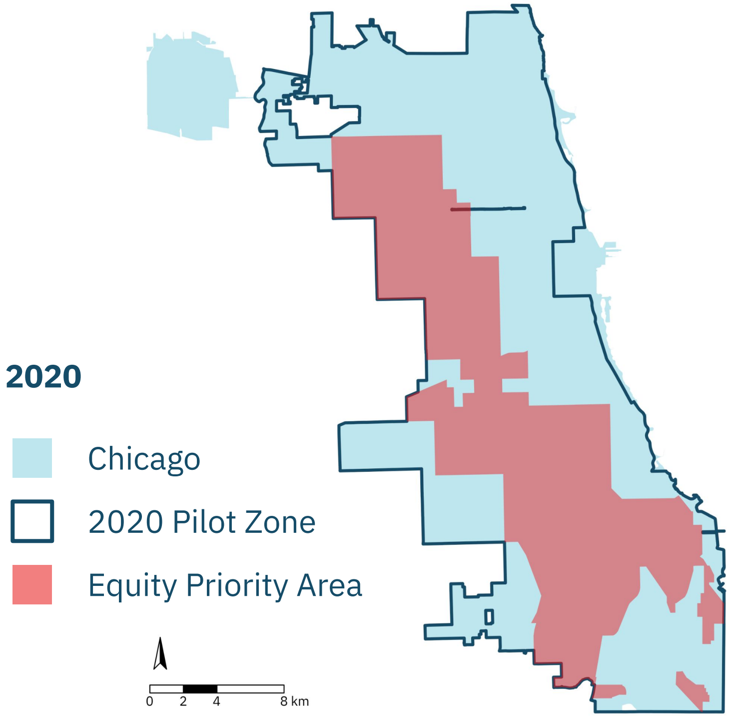


In order to assess the viability of an e-scooter share program in Chicago, the city ran two consecutive pilot projects in 2019 and 2020.

The 2019 scooter pilot was limited in scope to neighborhoods on the northeast side of the city. An assessment of the 2019 study was that **e-scooter parking was a problem**, with a high volume of 311 calls, and that **e-scooter riders were much whiter and wealthier than Chicago as a whole.**

Source: Chicago Data Portal, 2019 E-Scooter Pilot Evaluation (Chicago DOT)

Chicago's 2019 and 2020 E-Scooter Pilot Programs



Source: Chicago Data Portal, 2020 E-Scooter Pilot Evaluation (Chicago DOT)

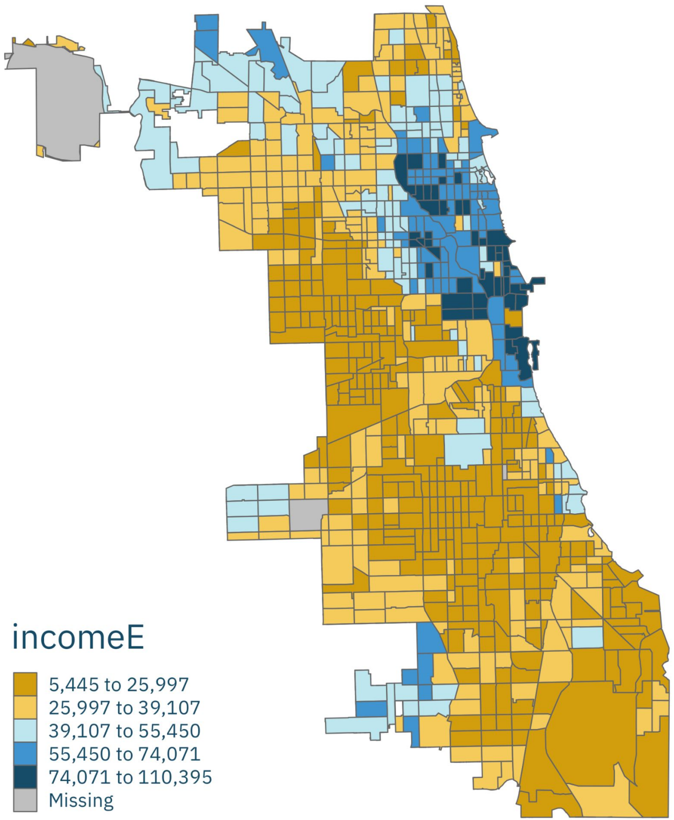
The 2020 e-scooter pilot project vastly expanded in scope, encompassing the entire city with the exception of the Loop and O'Hare. This pilot also featured two main policy interventions in order to improve equity, safety, and operations:

1. **Equity Priority Area:** Defined by Census tracts with low median incomes and poor Divvy or CTA coverage, vendors were required to distribute at least 50% of their fleet in the EPA on a daily basis or face fines. 150,000 rides, or 23% of total riders, originated from the EPA.

2. **"Lock-to" requirements:** E-scooters were required to be locked to bike parking or a fixed object. This reduced 311 calls by 75% compared to the 2019 pilot.

Mapping median income by Census tract

To the right is a map of median household income by Census tract in Chicago. Higher median incomes are concentrated around the Loop and the north shore, and lower median incomes are concentrated to the south and east. **The area where incomes are less than $40,000 maps closely to the Equity Priority Area described on the previous slide.**

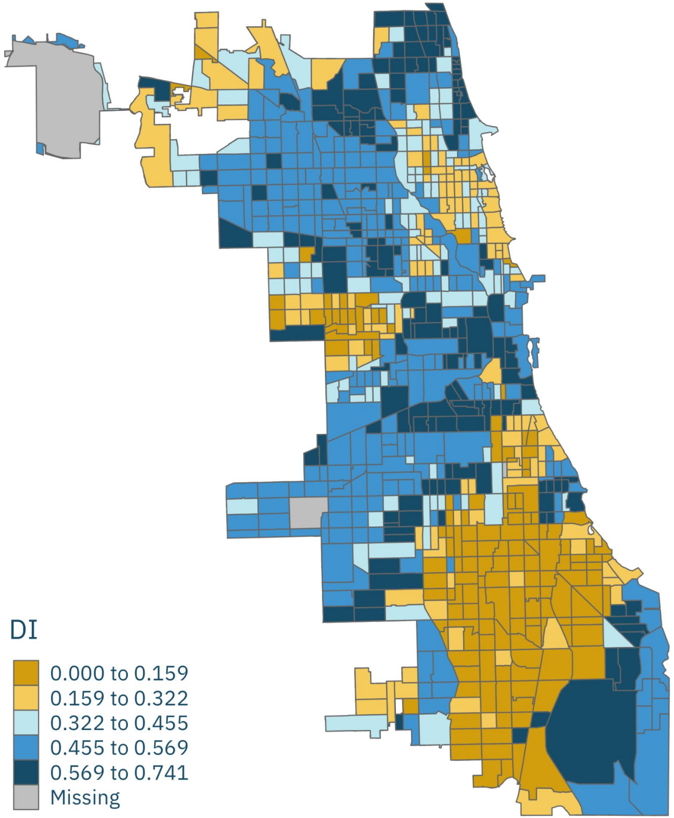


Source: Chicago Data Portal, U.S. Census Bureau

Mapping Diversity Index (DI) by Census tract

To the right is a map of a diversity index (DI) for each Census tract in Chicago. A diversity index indicates the **probability (from 0 to 1) that two people chosen at random will be from a different racial or ethnic group**. DI tends to be lowest in the majority Black South Side, majority Hispanic or Latino neighborhoods to the east, and the majority white north shore neighborhoods.

Source: Chicago Data Portal, U.S. Census Bureau



Price: Scooter vs Bike

Transportation literature has established that **price tends to be the single most influential factor in mode choice**. In assessing bike share versus e-scooter share, we wanted to first and foremost consider the impact that price might have.

We found, as is described in detail below, that while e-scooters are more expensive than bike share as a non-member, an e-scooter membership is cheaper than a bike share membership. **Since the difference in price is not consistently higher for e-scooters or bikes, we hypothesized that price was not the dominant factor in choosing between e-scooters or bikes** and that further investigation needed to be done into what factors are behind that choice.

Price Category	Member	Non-member
E-scooter	$5 annually: *$0 to unlock, $0.25/minute*	$1 to unlock, $0.39/minute
Bike (Divvy)	$11/month *Unlimited rides*	$1 to unlock, $0.17/minute
E-bike (Divvy)	$11/month: *$0 to unlock, $0.17/minute*	$1 to unlock, $0.42/minute

Sources: Giuliano 1995; Scooter Sharing in Chicago (chicago.gov)

RESEARCH QUESTION #1

Were **policy and operations changes** made between the 2019 and 2020 e-scooter pilot projects—such as establishing an Equity Priority Area and implementing lock-to requirements—**effective in meeting equity goals of the 2020 pilot?**

RESEARCH QUESTION #2

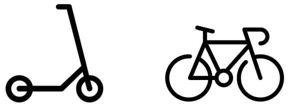
What combination of socioeconomic characteristics result in **higher odds of starting an e-scooter or bike share trip** in a given Census tract?

Data sources

Data Set	Source	Unit of analysis	Variables
E-Scooter Trips – 2019	City of Chicago Data Portal	Trip	• Start Census tract • End Census tract • Trip distance & duration
E-Scooter Trips – 2020	City of Chicago Data Portal	Trips by Census tract start-end pair	• Trip count by tract pair • Trip Start and end Centroids (also by tract)
Divvy Trips 2020 Q1	divvybikes.com historical trip data	Trip	• Start station • End station • Member or casual
American Community Survey (5-year)	U.S. Census Bureau	Census tract	• Race & ethnicity • Age • Median income • Commute mode choice

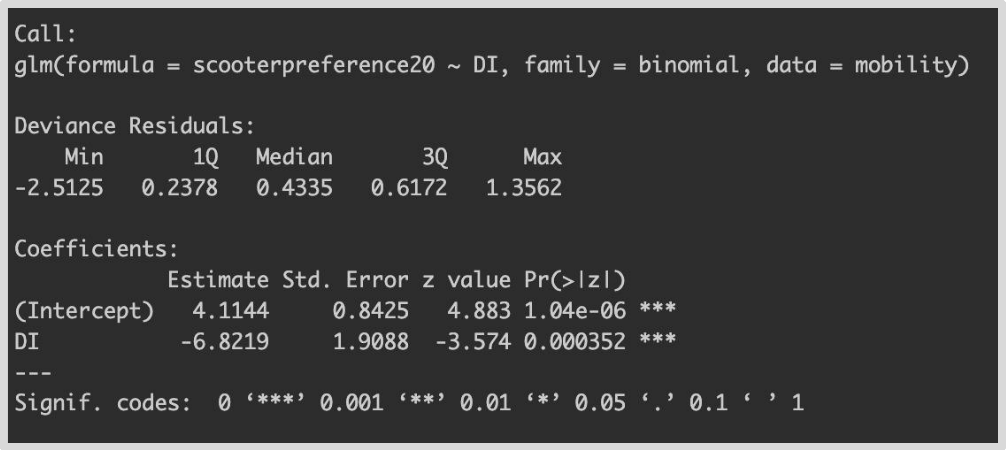
MODEL #1

Likelihood of a Census tract generating more e-scooter trips than bike trips in 2020



$$\textit{Scooter Preference} = 4.11 - 6.82(\textit{Diversity Index})$$

Using a reverse stepwise variable selection process, we took predictor variables out of our model until only the statistically significant ones remained. Then, we removed less powerful predictor variables to maximize the magnitude of the remaining coefficients. The right describes the summary of the leanest and strongest model.



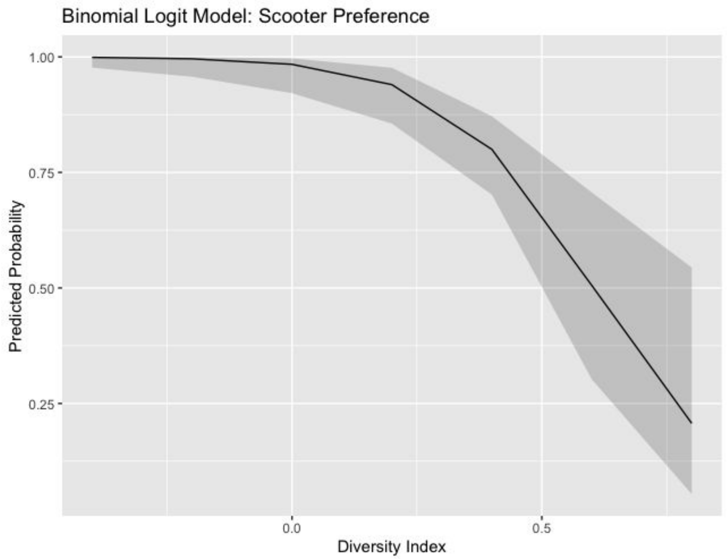
```
Call:
glm(formula = scooterpreference20 ~ DI, family = binomial, data = mobility)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.5125   0.2378   0.4335   0.6172   1.3562

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   4.1144     0.8425   4.883 1.04e-06 ***
DI           -6.8219     1.9088  -3.574 0.000352 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

MODEL #1

Likelihood of a Census tract generating more e-scooter trips than bike trips in 2020

Scooter Preference = 4.11 – 6.82(Diversity Index)

In our highest performing model, only the Diversity Index remained. **The log-odds of a Census tract generating more e-scooter trips than bike trips in 2020 decreases by 6.82 between a DI of 0 and 1.** Although DI was significant, other variables which described race or ethnicity were not. This model predicts that areas with the greatest Black, Hispanic, or white populations are more likely to take more e-scooter than bike trips. This might be explained by the fact that **whiter, wealthier census tracts along the north shore are consistently taking more e-scooter than bike trips**, or that e-scooters are **providing opportunities for mobility in transit deserts** in historically segregated, disinvested areas of Chicago.



MODEL #2

Likelihood of a Census tract generating greater than average e-scooter trips in 2020

Above Average Scooters = -6.6 + 1.9(income)

Using a reverse stepwise variable selection process, we took predictor variables out of our model until only the statistically significant ones remained. Then, we removed less powerful predictor variables to maximize the magnitude of the remaining coefficients. The right describes the summary of the leanest and strongest model.

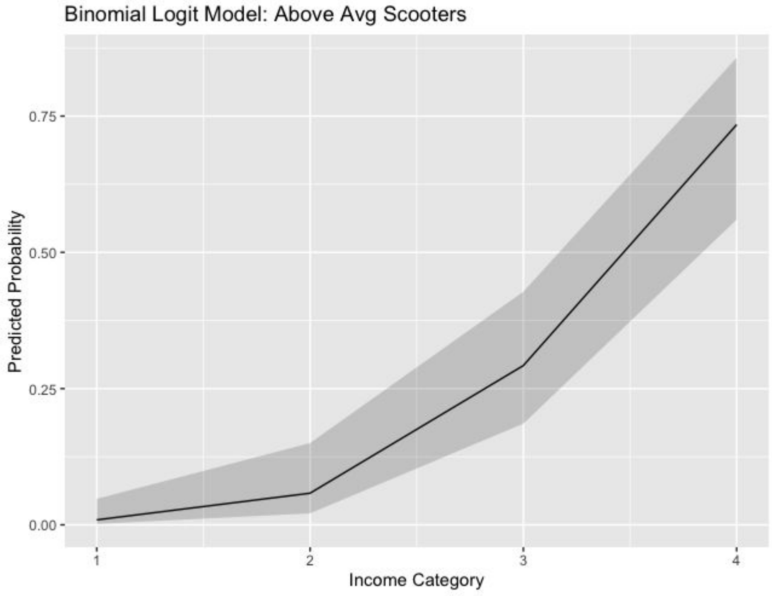
```
Call:
glm(formula = above_avg_scooter ~ income_cat, family = binomial,
    data = mobility)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.6284  -0.3460  -0.1354   0.7857   2.3856

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -6.5883     1.2097  -5.446 5.14e-08 ***
income_cat    1.9013     0.3612   5.264 1.41e-07 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

MODEL #2

Likelihood of a Census tract generating greater than average e-scooter trips in 2020

Above Average Scooters = -6.6 + 1.9(income)

In our highest performing model, only income category remained. **The log-odds of a Census tract generating greater than average e-scooter trips in 2020 increases by 1.9 for each increase in income category.** Although e-scooter and bike share price isn't significantly different, e-scooters are more expensive than walking or taking transit. Higher income Census tracts are likely to have better maintained roads and more safe bike infrastructure, which can tip the scales in someone deciding to make an active transit trip versus one by car or transit.



MODEL #3a

Likelihood of a Census tract generating more e-scooter trips in 2020 than 2019

More Scooters in 2020 (than 2019) = -4.9 + 2.08(above average Hispanic) + 2.28(above average Black) - 0.008(Walk to work)

Using the same backwards stepwise approach as the previous two model, the table to the right describes the summary of the leanest and strongest model. The log-odds of a Census tract generating more trips in 2020 than 2019 increased by **2.08 if the tract had a higher share of Hispanic residents than the city** and by **2.28 if the tract had a higher share of Black residents than the city.**

```
Call:
glm(formula = big_scooter_year ~ above_avg_hisp + above_avg_black +
    walkE, family = binomial, data = mobility)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.8530  -0.8066   0.5544   0.7359   2.8940

Coefficients:
                 Estimate Std. Error z value Pr(>|z|)
(Intercept)     -0.486708   0.488575  -0.996 0.319163
above_avg_hisp   2.081852   0.546623   3.809 0.000140 ***
above_avg_black  2.281867   0.619871   3.681 0.000232 ***
walkE           -0.008377   0.003944  -2.124 0.033699 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

MODEL #3b

Likelihood of a Census tract generating more e-scooter trips in 2020 than 2019

More scooters in 2020 (than 2019) = 4.2 - 0.009(walk to work) - 1.27 (income bracket)

Using the same backwards stepwise approach as the previous two model, the table to the right describes the summary of the leanest and strongest model. The log-odds of a Census tract generating more trips in 2020 than 2019 decreased by **0.009 for each percent of residents who walked to work** and by **1.27 for each consecutive income bracket.**

```
Call:
glm(formula = big_scooter_year ~ walkE + income_cat, family = binomial,
    data = mobility)

Deviance Residuals:
    Min       1Q    Median       3Q      Max
-2.3274  -0.7026   0.3294   0.6939   3.0494

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)  4.190898   0.808407   5.184 2.17e-07 ***
walkE       -0.008523   0.003695  -2.306   0.0211 *
income_cat  -1.270121   0.266118  -4.773 1.82e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

MODEL #3

Likelihood of a Census tract generating more e-scooter trips in 2020 than 2019

A. *More Scooters in 2020 (than 2019) = -4.9 + 2.08(above average Hispanic) + 2.28(above average Black) - 0.008(Walk to work)*

B. *More scooters in 2020 (than 2019) = 4.2 - 0.009(walk to work) - 1.27 (income bracket)*

Model 3a suggests that Census tracts with above average share of Black or Hispanic residents were more likely to ride e-scooters in 2020 than 2019. **This might indicate that the Equity Priority Area was effective in increasing e-scooter riders of color, but it also could indicate who had a greater need to continue taking trips during early months of the pandemic.**

This potential “covariance” with the pandemic is reinforced by Model 3b. Census tracts with higher median incomes which had a higher share of people who walk to work were likely to take less trips in 2020 than 2019, which might reflect the fact that higher income, white-collar jobs were more likely to work from home and therefore take less trips overall.

Comparison between models

The table on the right is a summarization of the three different modeling angles we explored and the variables which had the strongest predictive power.

Race, ethnicity, and income were powerful predictive factors across the board. Share of commuters who walked or took transit to work were much less powerful, but still statistically significant in nearly every case.

Even though our models indicate that the Equity Priority Area made some difference in promoting e-scooter equity, we ultimately can't rule out the pandemic as a covarying factor that explains the variation from 2019 to 2020.

Model	Strongest Predictors
1. Likelihood of a Census tract generating more e-scooter trips than bike trips in 2020	Diversity Index
2. Likelihood of a Census tract generating greater than average e-scooter trips in 2020	Income category
3. Likelihood of a Census tract generating more e-scooter trips in 2020 than 2019	Income bracket, walk to work, above average Hispanic and Black populations

Limitations & potential sources of error

1. Spatial patterns

Due to the scope of our project and limitations by trip data aggregation, **we weren't able to interpret spatial data and patterns,** such as distance from CTA rail station or Divvy station which might be important explanatory variables in comparing e-scooter and bike share use.

2. Aggregated data

One of the biggest constraints in our analysis was the fact that the 2020 Chicago e-scooter pilot trip data set was in Census tract pairs, and **we had to aggregate other trip data sets to this level in order to have the same unit of analysis**. While Census tract is a relatively granular level of geography to analyze, it still locked in our analysis to only look at this level.

Limitations & potential sources of error

3. Price

While we discussed how neither e-scooter share nor bike share were more expensive than the other across the board, but **Census tract level aggregation eliminated trip-level information on whether rides were taken by members or non-members,** which is something we would have liked to take into consideration as a proxy for price.

4. COVID

We would be remiss not to discuss how the 2020 e-scooter pilot project took place in the early months of the pandemic. Since the **pandemic so deeply affected travel and commuting behavior**, and could have just as easily explained the changes in e-scooter ridership from 2019 to 2020 as the policy interventions could, so we **can't in good faith claim that these policy interventions alone made an equity impact in the 2020 pilot.**

Implications for e-scooter & bike share data

E-scooters are a relatively young mode, and data collection has proved to be a challenge across the country. E-scooters are often lumped into an “other” category, making it difficult to track critical questions like traffic fatalities. This makes responsive policy interventions much more difficult to implement.

Pre-aggregated data might be an important privacy consideration, as it was in Chicago. The challenge here is that the potential for peer cities like Philadelphia or Boston to be able to learn from Chicago is significantly diminished. **How can we balance questions of privacy and transparency in micromobility data?**

A common talking point in opposition to e-scooters is that they displace transit trips. In our modeling, e-scooter prevalence tended to have a weakly positive, but significant, relationship with taking transit to work. **More work should be done to understand how the two can be better connected, but painting them to be plainly in opposition is unfounded.**

Thank you!