

Summary Report ([link](#)), and the City of Austin’s Director Rules for Deployment and Operation of Shared Small Vehicle Mobility Systems ([link](#)) for the targeted rides per scooter per day metrics. (We calculate the utilization target for Austin TX as $100 \times (3 \text{ rides per scooter-day}) \times (18.5 \text{ minutes per ride}) / (840 \text{ minutes per scooter-day})$. We calculate other utilizations similarly.)

6. In fact, this exact scenario played out at 8:03 pm on May 8, 2021, and the rider did indeed pick one of the 10 Bird scooters. Earlier on the same day, around 7:02 am, a rider was standing on the nearby corner of Wyandotte and 10th Street looking at 4 Bird scooters and 8 Spin scooters, and picked a Spin scooter. We use the set of all such instances to structurally estimate micro rider choice in Section 5.

7. Fleet-sizing decisions are long-term: We run an ordinary least squares regression at the operator-date level of fleet size on month fixed effects for each of Baltimore, MD, Chicago, IL, Kansas City, MO, and Louisville, KY. These four regressions’ R-squared statistics are 0.94, 0.96, 0.90, and 0.94, respectively. In other words, the month and city together explain over 90% of the inter-temporal variation in fleet sizes. Based on our conversations with executives, fleet size decisions are revisited at permit renewals, every 6 to 12 months. Between permit renewals, operators keep their fleets consistent, except for events like festivals or extreme weather.

Operators tend to put their scooters in the same spots: We run an ordinary least squares regression at the operator-date-neighborhood level of an operator’s 9am log-fleet size on the operator’s competitors’ total 9am log-fleet size and date fixed effects, for each of Baltimore, Chicago, Kansas City, MO, and Louisville, KY. The estimated coefficients of the operator’s competitors’ total 9am log-fleet size in these four regressions are 0.43, 0.86, 0.56, and 0.44, respectively (all significant at $p = 0.001$ level). In other words, controlling for simultaneous temporal shocks to fleet sizes, the more competitor scooters in a spot, the more scooters an operator puts in that spot.

8. In theory, our focal mechanism—interaction of rider choice and competition—could lead to further oversupply through an additional channel: incumbent operators colluding to deter entry. We thank our Associate Editor for pointing out this channel.

Assume that $\beta = 1$, that demand is uniformly distributed in $(0, M)$, and that the fixed cost of operating in a market is k . Then, the profit of each of N (symmetric) operators playing a single-shot equilibrium is given by

$$\pi_N^* = AB^2/(N+1)^2 - k,$$

where $A = r/2M$ and $B = 2M(1 - c/r)$. Moreover, the competing fleet size that makes an operator’s single-shot optimal profit from entry equal to zero is given by $\bar{s} = B - 2\sqrt{k/A}$. And if N operators split $\bar{s}$ between them N -ways, then each of their profits equals

$$\bar{\pi}_N = A((B/2)^2 - (B/2 - 2\sqrt{k/A})^2)/N - k.$$

It is easy to check that if $AB^2 > 4k$, then for N large enough $\bar{\pi}_{N+1} > \pi_N^*$. That is, for N large enough it is more profitable for N operators to each play $\bar{s}/N$ and saturate the market, than to share the market with an $N + 1$ -th operator.

Next, we demonstrate that this collusion to deter entry is sustainable in a repeated game. In particular, consider the following strategy profile for N incumbent operators and an $N + 1$ -th, potential-entrant operator:

Incumbent operators ($i = 1, \dots, N$):

- if $\sum_{i=1}^N s_i < \bar{s}$ has been played at least once before, play $s^*(1, N+1)/(N+1)$.
- if $\sum_{i=1}^N s_i < \bar{s}$ has never been played before, play $\bar{s}/N$.

Potential entrant ($i = N + 1$):

- if $\sum_{i=1}^N s_i < \bar{s}$ has been played at least once before, play $s^*(1, N+1)/(N+1)$.
- if $\sum_{i=1}^N s_i < \bar{s}$ has never been played before, play 0.

We formally prove that the above strategy profile is a subgame perfect equilibrium for discount factors δ away from zero (but below one) using the single-deviation principle.

Specifically, it is clear that if $\sum_{i=1}^N s_i < \bar{s}$ has been played at least once then deviating from $s^*(1, N+1)/(N+1)$ is not profitable for any operator—the potential entrant has already entered, so everyone might as well play the single-shot equilibrium. It is also clear that, as long as the incumbent operators are holding steady with their aggregate fleet size of $\bar{s}$, the $i = N+1$ operator has no incentive to enter. This leaves the last case where $\sum_{i=1}^N s_i < \bar{s}$ has never been played, but operator $i = 1$ is considering deviating and playing $s' < \bar{s}/N$ with corresponding single-shot profit π' . In that case, operator $i = 1$'s total payoff gains from deviating for one period would be

$$\pi' + \frac{\delta}{1-\delta} \pi_{N+1}^* - \frac{\bar{\pi}_N}{1-\delta},$$

which, for $\delta > (\pi' - \bar{\pi}_N)/(\pi' - \pi_{N+1}^*)$, would be negative.

9. When $\beta = 0$, the equilibrium aggregate fleet-size is given by $s^*(0, N) = \bar{F}^{-1}(c/(rm))$. Therefore, the equilibrium aggregate fleet size always hits service level $c/(rm)$. And utilization is more-or-less tied to service level. Take page 8's example, where $\beta = 0$, $F(z) = 1 - \exp(-z/100)$, $m = 1$, and $c/r = 0.25$. In this example, the aggregate fleet size is $s^*(0, N) = 138$ scooters and the utilization is 1.5929%. Doubling demand, i.e., using $\tilde{F}(z) = 1 - \exp(-z/200)$, increases the aggregate fleet size to 277 scooters but keeps utilization at 1.5930%.
10. Scooter specifications have changed, and battery capacities have improved over time. We used the average battery life provided by Spin ([link](#)) and Bird ([link](#)).
11. See The Verge's article "Lime adds Wheels shared e-bikes to its app as it seeks to become a one-stop shop for mobility" ([link](#)). The Press Release by Bird "Bird Acquires Spin, Now North America's Largest Micromobility Operator By Market Share" ([link](#)), The Crunchbase News's article "Bird Acquires German Scooter Startup Circ, Adds \$75M To Series D" ([link](#)), and TechCrunch's article "Bird confirms acquisition of Scoot" ([link](#)).
12. This finding is consistent with what we have observed in the scooter market over the last four years. Scooter designs have improved (including battery technologies—see, e.g., Techcrunch's article "Next-gen Bird Three scooter comes with bigger battery and better software" [link](#)), yet aggregate fleet sizes have not decreased.
13. Three notes: First, although most of the variation in the aggregate fleet size is generated by the disruption itself, as is evident from Figure 7, some of the remaining variation could still be endogenous—e.g., operators still slightly increase their fleet sizes over the weekend. Fortunately, this remaining endogeneity clearly creates a positive conditional correlation between supply and demand, which means it leads to an over-estimate of λ . Second, we identified another four such fleet-size disruption events: three from Atlanta, GA, and one from Baltimore, MD. We focus our analysis on the San Francisco, CA disruption, because the other four occurred after the start of the Covid-19 pandemic. The results we present replicate in the other four disruptions as well. Moreover, pooling these events further shrinks the elasticity estimate and its confidence interval towards zero—see Figure 7's caption. Third, although demand does not respond much to the 10–20% supply changes we observe, we cannot rule out that it would respond to larger changes, e.g., to a sudden 50–60% supply reduction.
14. Transportation departments we interviewed explained that currently they set maximum deployment caps to prevent extreme, unreasonable deployments rather than tightly control supply. Indicatively, in Austin, TX, the median ratio of daily deployed scooters to the cap between January 1, 2019, and March 1, 2020, was just 0.47.

A. Proof of the Proposition

We present all proofs for $m = 1$. Extending the analysis to general m is straightforward. To see why, note that the i -th operator's optimization problem

$$\max_{s_i \geq 0} \int_0^\infty r \min(ms_i, zs_i^\beta / \sum_{j=1}^N s_j^\beta) dF(z) - cs_i,$$

is equivalent to

$$\max_{x_i \geq 0} \int_0^\infty r \min(x_i, zx_i^\beta / \sum_{j=1}^N x_j^\beta) dF(z) - (c/m)x_i.$$

In other words, one can perform the analysis with rides instead of scooters, as long as they convert variable costs from the per-scooter basis to the per-ride basis.

Equilibrium for $\beta = 0$

For $\beta = 0$, the i -th operator maximizes

$$\pi(s_i|0) = \int_0^\infty r \min(s_i, z/N) dF(z) - cs_i,$$

whose derivative with respect to s_i equals

$$\pi'(s_i|0) = r\bar{F}(Ns_i) - c,$$

where $\bar{F}(s) = 1 - F(s)$.

Since (i) $\pi'(s|0)$ is strictly decreasing in s_i , (ii) $\pi'(0|0) = r - c > 0$, and (iii) $\pi'(\infty|0) = -c < 0$, operator i 's optimal fleet size is the unique s_i^* that solves the first-order condition $\pi'(s_i^*|0) = 0$, or, equivalently,

$$s_i^* = \bar{F}^{-1}(c/r)/N.$$

Therefore, the unique equilibrium aggregate fleet size when $\beta = 0$ is given by

$$s^*(0, N) = \bar{F}^{-1}(c/r),$$

which is constant in N .

Equilibrium for $\beta = 1$

For $\beta = 1$, the i -th operator maximizes

$$\pi(s_i|1) = \int_0^\infty r \min(s_i, zs_i / \sum_{j=1}^N s_j) dF(z) - cs_i,$$

whose derivative with respect to s_i equals

$$\pi'(s_i|1) = r \left(1 - s_i / \sum_{j=1}^N s_j\right) \int_0^{\sum_{j=1}^N s_j} \bar{F}(z) dz / \sum_{j=1}^N s_j + r \left(s_i / \sum_{j=1}^N s_j\right) \bar{F}\left(\sum_{j=1}^N s_j\right) - c,$$

where $\bar{F}(s) = 1 - F(s)$.

Since (a) $s_i / \sum_{j=1}^N s_j$ is strictly increasing in s_i , (b) $\int_0^s \bar{F}(z) dz / s > \bar{F}(s)$, and (c) $\int_0^s \bar{F}(z) dz / s$ and $\bar{F}(s)$ are strictly decreasing in s , we have that (i) $\pi'(s_i|1)$ is strictly decreasing in s_i . And since we also have that (ii) $\pi'(0|1) = r - c > 0$ and (iii) $\pi'(\infty|1) = -c < 0$, operator i 's optimal fleet size is the unique s_i^* that solves the first-order condition $\pi'(s_i^*|1) = 0$.

The unique equilibrium aggregate fleet size, $s^*(1, N)$, is the unique solution to the average first-order condition across all N operators

$$(1 - 1/N) \int_0^{s^*(1, N)} \bar{F}(z) dz / s^*(1, N) + (1/N) \bar{F}(s^*(1, N)) = c/r,$$

and this unique solution is increasing in N , because $(1 - 1/N) \int_0^s \bar{F}(z) dz / s + (1/N) \bar{F}(s)$ is strictly decreasing in s and strictly increasing in N .

Equilibrium for $\beta \rightarrow \infty$

For $\beta \rightarrow \infty$, the i -th operator maximizes

$$\pi(s_i|\infty) = \int_0^\infty r \min(s_i, z) 1_{(s_i = \max_{j=1}^N s_j)} / \sum_{j=1}^N 1_{(s_j = \max_{k=1}^N s_k)} dF(z) - cs_i.$$

In what follows it is useful to define

$$\pi(s) = \int_0^\infty r \min(s, z) dF(z) - cs,$$

and note that, since (i) $\pi'(s) = r\bar{F}(s) - c$ is strictly decreasing in s (where $\bar{F}(s) = 1 - F(s)$), (ii) $\pi'(0) = r - c > 0$, (iii) $\pi'(\infty) = -c < 0$, (iv) $\pi(0) = 0$, and (v) $\pi(\infty) = -\infty$, there exists a unique $\bar{s} > 0$ such that $\pi(s) > 0$ for $s \in (0, \bar{s})$, $\pi(\bar{s}) = 0$, and $\pi(s) < 0$ for $s \in (\bar{s}, \infty)$.

For $N = 1$, by (i), (ii), and (iii), the optimal fleet size is the unique $s^*(\infty, 1)$ that solves the first-order condition $\pi'(s^*(\infty, 1)) = 0$, or, equivalently,

$$s^*(\infty, 1) = \bar{F}^{-1}(c/r).$$

For $N > 1$:

1. There exists no equilibrium in which $\max_{j=1}^N s_j > \bar{s}$, because at least one of the operators that achieve this maximum would prefer to play $s_i = 0$, and make zero profits instead of negative profits.

2. There exists no equilibrium in which $\max_{j=1}^N s_j = \bar{s}$ and $\sum_{j=1}^N 1_{(s_j = \max_{k=1}^N s_k)} > 1$, because one of the operators that achieve this maximum would prefer to play $s_i = 0$ and make zero profits instead of negative profits.
3. There exists no equilibrium in which $\max_{j=1}^N s_j = \bar{s}$ and $\sum_{j=1}^N 1_{(s_j = \max_{k=1}^N s_k)} = 1$, because (a) if at least one of the operators that do not achieve this maximum currently plays $s_i > 0$ then that operator would prefer to play $s_i = 0$ and make zero profits instead of negative profits, and (b) if all operators that do not achieve this maximum currently play zero, then the single operator that achieves this maximum would prefer to play $\bar{s} - \epsilon$ (instead of $\bar{s}$) and make positive profits instead of zero profits.
4. There exists no equilibrium in which $\min_{j=1}^N s_j < \max_{j=1}^N s_j < \bar{s}$, because at least one of the operators that achieve this minimum would prefer to play $s_i = \max_{j=1}^N s_j + \epsilon$ and make positive profits instead of non-positive profits.
5. There exists no equilibrium in which $\min_{j=1}^N s_j = \max_{j=1}^N s_j = s < \bar{s}$, because at least one of the operators would prefer to play $s_i = s + \epsilon$ and make profits $\int_0^\infty r \min(s + \epsilon, z) dF(z) - c(s + \epsilon) \xrightarrow{\epsilon \rightarrow 0} \int_0^\infty r \min(s, z) dF(z) - cs$ instead of making profits $\int_0^\infty r \min(s, z/N) dF(z) - cs$.

In summary, there exists no equilibrium for $N > 1$.

Equilibrium for general β

For general β , the i -th operator maximizes

$$\pi(s_i|\beta) = r \int_0^\infty \min(s_i, z s_i^\beta / \sum_{j=1}^N s_j^\beta) dF(z) - cs_i,$$

whose derivative with respect to s_i equals

$$\pi'(s_i|\beta) = r\beta(1 - w(s_i)) \int_0^{s_i/w(s_i)} \bar{F}(x) dx / (s_i/w(s_i)) + r(1 - \beta(1 - w(s_i))) \bar{F}(s_i/w(s_i)) - c,$$

where $\bar{F}(s) = 1 - F(s)$ and $w(s_i) = s_i^\beta / \sum_{j=1}^N s_j^\beta$.

We already analyzed the cases when $\beta = 0$, $\beta = 1$, and $\beta \rightarrow \infty$. We next analyze the case when $\beta \in (0, 1)$ and the case when $\beta \in (1, \infty)$.

For $\beta \in (0, 1)$, we have that (a) $w(s_i)$ and $s_i/w(s_i)$ are strictly increasing in s_i , (b) $\int_0^s \bar{F}(z) dz/s > \bar{F}(s)$, and (c) $\int_0^s \bar{F}(z) dz/s$ and $\bar{F}(s)$ are strictly decreasing in s . Therefore, (i) $\pi'(s_i|\beta)$ is strictly decreasing in s_i . And since we also have that (ii) $\pi'(0|\beta) = r - c > 0$ and that (iii) $\pi'(\infty|\beta) = -c < 0$, it follows that operator i 's optimal fleet size is the unique s_i^* that solves the first-order condition $\pi'(s_i^*|\beta) = 0$.

Averaging these first-order conditions across all N operators and imposing symmetry, we get that the unique symmetric equilibrium aggregate fleet size when $\beta \in (0, 1)$ is given by the unique $s^*(\beta, N)$ that solves

$$\beta(1 - 1/N) \int_0^{s^*(\beta, N)} \bar{F}(z) dz / s^*(\beta, N) + (1 - \beta(1 - 1/N)) \bar{F}(s^*(\beta, N)) = c/r,$$

and this unique solution is increasing in N , because $\beta(1 - 1/N) \int_0^s \bar{F}(z) dz / s + (1 - \beta(1 - 1/N)) \bar{F}(s)$ is strictly decreasing in s and strictly increasing in N .

For $\beta \in (1, \infty)$, we have that $\pi'(0|\beta) = \pi'(\infty) = -c < 0$, and we *numerically* verify that there is an $\hat{s}$ such that $\pi'(s|\beta)$ is increasing for $s \in (0, \hat{s})$ and decreasing for $s \in (\hat{s}, \infty)$. Therefore, operator i 's optimal fleet size is zero if $\pi'(\hat{s}|\beta) \leq 0$, and is either zero or the largest of the two solutions of the first-order condition $\pi'(s|\beta) = 0$ if $\pi'(\hat{s}|\beta) > 0$. (In fact, we can analytically prove that $\pi'(s|\beta)$ is decreasing for $s \in (0.5/(1 - 1/\beta), \infty)$; but fully characterizing $\pi'(s|\beta)$'s monotonicity is tricky.)

Averaging these first-order conditions across all N operators and imposing symmetry, we get that any non-zero symmetric equilibrium aggregate fleet size, $s^*(\beta, N)$, would solve

$$\beta(1 - 1/N) \int_0^{s^*(\beta, N)} \bar{F}(z) dz / s^*(\beta, N) + (1 - \beta(1 - 1/N)) \bar{F}(s^*(\beta, N)) = c/r.$$

We *numerically* verify that this equation has at most one solution for every N , and that this solution, if it exists, is increasing in N .

B. Analytical details for counterfactuals

Estimating β

For our main specification on page 12, we choose the β that maximizes the empirical likelihood function

$$L(\beta) = \prod_j (n_{1j}^\beta / (n_{1j}^\beta + n_{2j}^\beta))^{u_{1j}} (n_{2j}^\beta / (n_{1j}^\beta + n_{2j}^\beta))^{u_{2j}},$$

where: j indexes rides; n_{1j} and n_{2j} count the number of operator-1 and operator-2 devices within 100 meters of j 's start location, respectively; and u_{1j} and u_{2j} indicate that j 's rider picked operator 1 and operator 2, respectively. And since $n_{1j}^\beta / (n_{1j}^\beta + n_{2j}^\beta) = \exp(\beta \log(n_{1j}/n_{2j})) / (\exp(\beta \log(n_{1j}/n_{2j})) + 1)$, finding the β that maximizes $L(\beta)$ is the same as running a logit regression of u_{1j} on $\log(n_{1j}/n_{2j})$.

Adding brand preferences to the model makes the probability operator 1 is chosen for ride j equal to $\exp(\log(\alpha_1/\alpha_2) + \beta \log(n_{1j}/n_{2j})) / (\exp(\log(\alpha_1/\alpha_2) + \beta \log(n_{1j}/n_{2j})) + 1)$. Accordingly, estimating α_1 , α_2 , and β is the same as running a logit regression of u_{1j} on an intercept and $\log(n_{1j}/n_{2j})$.

Estimating c/r

With two asymmetric operators, the i -th operator maximizes

$$\int_0^\infty r_i \min(ms_i, zs_i^\beta/(s_1^\beta + s_2^\beta)) dF(z) - c_i s_i,$$

whose derivative with respect to s_i equals

$$\begin{aligned} r_i m \beta (1 - w_i(s_1, s_2)) \int_0^{ms_i/w_i(s_1, s_2)} \bar{F}(x) dx / (ms_i/w_i(s_1, s_2)) \\ + r_i m (1 - \beta (1 - w_i(s_1, s_2))) \bar{F}(ms_i/w_i(s_1, s_2)) - c_i, \end{aligned}$$

where $\bar{F}(s) = 1 - F(s)$ and $w_i(s_1, s_2) = s_i^\beta / (s_1^\beta + s_2^\beta)$.

Therefore, setting

$$\begin{aligned} H_i(s_1, s_2) = m \beta (1 - w_i(s_1, s_2)) \int_0^{ms_i/w_i(s_1, s_2)} \bar{F}(x) dx / (ms_i/w_i(s_1, s_2)) \\ + m (1 - \beta (1 - w_i(s_1, s_2))) \bar{F}(ms_i/w_i(s_1, s_2)), \end{aligned}$$

we can write the i -th operator's first-order condition as $H_i(s_1, s_2) = c_i/r_i$.

We estimate operator i 's cost-reward ratio using the observed $(\hat{s}_1, \hat{s}_2)$ and the estimated $\hat{\beta}$, $\hat{F}(\cdot)$, and $\hat{m}$, with $H_i(\hat{s}_1, \hat{s}_2)$. Then we check that $(\hat{s}_1, \hat{s}_2)$ is indeed an equilibrium within the model by maximizing operator 1's objective given the estimated cost-reward ratio and the observed $\hat{s}_2$ and verifying the maximizer is indeed $\hat{s}_1$, and then doing the same for operator 2.

The process is exactly the same with brand preferences, except that $w_i(s_1, s_2) = \alpha_i s_i^\beta / (\alpha_1 s_1^\beta + \alpha_2 s_2^\beta)$.

Counterfactual equilibria

With two asymmetric operators, calculating counterfactual equilibria requires solving the two operators' non-linear first-order conditions simultaneously. We tackle this problem by numerically minimizing the sum of these first-order conditions squared:

$$\min_{s_1, s_2} (H_1(s_1, s_2) - c_1/r_1)^2 + (H_2(s_1, s_2) - c_2/r_2)^2.$$

Then we check that the solution to this minimization problem, (s_1^*, s_2^*) , is indeed an equilibrium within the model by maximizing operator 1's objective given s_2^* and verifying the maximizer is indeed s_1^* , and then doing the same for operator 2. (The process works similarly for three operators.)

C. Empirical details

Constructing Figure 1

For Atlanta, GA, Chicago, IL, Denver, CO, San Francisco, CA, and Tempe, AZ we obtain ridership and fleet size data by contacting these cities' transportation departments. A row in these data sets

is a city–date, and the columns are the daily total operational fleet size, the daily total ridership, and the average trip duration. The time window for Atlanta, GA is January 24, 2019–February 28, 2021; for Chicago, IL it is June 15, 2019–October 15, 2019; for Denver, CO it is October 31, 2018–November 16, 2020; for San Francisco, CA it is November 01, 2018–February 26, 2021; and for Tempe, AZ it is February 27, 2019–March 24, 2021.

For Bloomington, IN, we obtain ridership and fleet size data using the city’s open data portal. Each row in this data set is a date, and the columns are the daily total operational fleet size, the daily total ridership, and the average trip duration. The time window for Bloomington is April 05, 2019–December 11, 2019.

For Austin, TX, we obtain ridership data using the city’s open data portal. Each row in this data set is a trip, and the columns are the device type, the start and end time, the start and end location, the trip duration, the trip distance, and an anonymized device ID. These device IDs are consistent within date; hence a lower bound on a date’s fleet size is the count of unique device IDs we observe among that date’s rides. (Lower bound because we only observe a scooter ID on a date if the corresponding scooter had at least one ride on that date.) The time window for Austin, TX is May 23, 2018–February 29, 2020.

For Louisville, KY and Kansas City, MO, we obtain ridership data using these cities’ open data portals. Both Louisville, KY’s and Kansas City, MO’s ridership data have the same format as Austin, TX’s, except that they do not include device IDs. Three operators operate in Louisville, KY—Bird, Lime, and Spin—and three in Kansas City—Bird, Spin and RideKC. To calculate daily fleet sizes, we connect to these operators’ application programming interfaces every 5 minutes, and then use the maximum number of scooters within operator–city–date. The time window for Louisville, KY is from June 07, 2020 to August 05, 2020; and for Kansas City, MO is from February 19, 2021 to May 14, 2021.

For the NYC Citi-Bike and Austin Metro Bike we obtain ridership data from these cities’ open data portals. Each row is a ride, and columns are the device type, the start and end times, the station ID, the trip duration, the trip distance, and the membership type. Both cities also publicly post operational fleet sizes in their bike-sharing reports. The time window for NYC Citi-Bike is June 01, 2019 to September 30, 2019, and for Austin Metro Bike it is June 02, 2017 to June 30, 2018.

We assume that after deployment each scooter spends 14 hours on the streets for the following reasons: (i) once deployed, scooters stay on the street until they are picked up for daily maintenance, (ii) Chicago, IL, Atlanta, GA, and Louisville, KY, do not allow scooter rides from midnight to 5 am, (iii) we have proprietary data from one of the biggest operators in the U.S. which point to a 14-hour average on-street time for scooters.

Constructing Figure 2

Each row in Austin, TX’s ridership data is a trip (uniquely identified by an anonymized trip ID), and the columns are an anonymized device ID (consistent within date), the device type (scooter or bike), the start and end time, the start and end location (defined by census tract and council district), the trip duration, and the trip distance.

The raw data contain 8,366,522 rides between April 3, 2018 and February 29, 2020. To construct our final sample, we drop (i) rides with a negative trip duration or a duration exceeding the scooters’ capacity and (ii) the first 6 weeks (April 3, 2018–May 17, 2018), when Lime and Bird deployed their devices overnight and got banned by the city. We end up with 8,023,918 rides across 631 days.

We contact the Austin, TX, Transportation Department to get the exact operator entry dates. After Bird and Lime, a total of 14 operators got a permit to operate in Austin, TX. One of these 14 operators did not launch any scooters, and another got a permit for only 20 scooters. We remove these two operators’ entry dates from the analysis. The remaining 12 operators’ entry dates are: June 1, 2018, June 8, 2018, June 14, 2018, July 24, 2018, October 1, 2018, October 17, 2018, October 23, 2018, November 13, 2018, December 13, 2018, December 18, 2018, October 24, 2019 and November 1, 2019.

Constructing the Kansas City, MO sample

In our raw sample we observe 90,307 rides over 142 dates and 123 neighborhoods. To construct our final sample we drop:

- 1. 14 dates on which we are missing at least 4 hours of scooter availability data due to server connectivity issues.
- 2. 116 neighborhoods with fewer than 500 rides with more than one operator’s scooters available within 100 meters from the ride’s origin within 10 minutes from the ride’s start time.
- 3. The “Country Club Plaza” neighborhood because the city imposed scooter deployment bans in that neighborhood during our observation window.
- 4. The winter season (December 8, 2020–February 20, 2021) because its demand patterns are very different from the rest of the time window.
- 5. Neighborhoods with fewer than 45 days of data.

In our final sample we observe 59,516 rides over 69 dates and 9 neighborhoods.

D. Additional exhibits



Figure A.1: Referenced on page(s) 1. A group of scooters outside the University of San Diego’s News Center ([link](#)). California Vehicle Code 407.5 defines a motorized scooter as “...any two-wheeled device that has handlebars, has either a floorboard that is designed to be stood upon when riding or a seat and footrests in place of the floorboard, and is powered by an electric motor. This device may also be designed to be powered by human propulsion.” In their first two years of operation, dockless scooters and dockless bikes had completed 125.5 million trips in the U.S., and 300 million trips globally. At the end of 2019 they were available in 626 cities across 53 countries. We obtained these ridership statistics from the National Association of City Transportation Officials’ reports “Shared Micromobility in the U.S.: 2018” ([link](#)) and “Shared Micromobility In The U.S.: 2019” ([link](#)), and Ernst and Young’s report “Micromobility: moving cities into a sustainable future” ([link](#)).

Source	City	Year	# Resp.	Commute/ Transit	Shopping/ Errands	Health/ Wellness	Social/ Ent.	Recreation/ Leisure	Other
Aarhaug et al. (2023)	Norway	2021	1,921	22.07	13.02		36.70	13.50	14.71
Baltimore City DOT (link)	Baltimore, MD	2018	3,406	36.60	16.40		34.90	9.10	3.00
Baltimore City DOT (link)	Baltimore, MD	2020	330	56.70	12.40		22.40	7.30	1.20
Bielniński and Ważna (2020)	Poland	2019	633	24.36	6.30	6.30	27.89	35.15	
CDOT (link)	Chicago, IL	2020	2,400	7.08	34.07	4.87	25.66	28.32	
Christoforou et al. (2021)	Paris, FR	2021	32	24.75	8.91		17.82	48.51	
City of Austin (link)	Austin, TX	2018	3,359	25.60	21.08	24.40	28.92		
Hardt and Bogenberger (2019)	Munich	2019	38	31.00	36.00			33.00	
Denver Public Works (link)	Denver, CO	2018	2,084	55.00	7.00		31.00	7.00	
Lyft (link)	US	2022	>1,000	22.03	17.18	6.17	23.35	31.28	
NABSA (link)	US & CA	2020–2023		25.00	18.00		31.00	26.00	
PBOT (link)	Portland, OR	2018	3,444	33.68	9.68	0.49	26.38	29.77	
PBOT (link)	Portland, OR	2019	1,588	51.41	9.57		20.35	18.67	
Populus (link)	Brookline, MA	2019	2,100	33.00	38.00		22.00		
Sanders et al. (2020)	Tempe, AZ	2019	1,256	25.35	4.23		34.51	29.58	6.34

Table A.1: Referenced on page(s) 1. Summary of scooter user surveys focusing on trip purposes. To standardize categories, we grouped the answers into six groups: commute/transit, shopping/errands, health/wellness, social/entertainment, recreation/leisure, and other.

Date	City	Operator	Initial Price (\$)	Updated Price (\$)
Mar-19	Washington D.C.	Bird	1+0.15	1+0.29
Mar-19	Washington D.C.	Lime	1+0.15	1+0.24
Mar-19	Washington D.C.	Bolt	0+0.15	0+0.30
Mar-19	Washington D.C.	Jump	0+0.15	0+0.25
Mar-19	Washington D.C.	Lyft	1+0.15	1+0.24
Mar-19	Washington D.C.	Skip	1+0.15	1+0.25
Mar-19	Washington D.C.	Spin	1+0.15	1+0.25
Mar-19	Indianapolis, IN	Bird	1+0.15	1+0.29
Mar-19	Indianapolis, IN	Lime	1+0.15	1+0.27
Mar-19	Austin, TX	Bird	1+0.15	1+0.25
Mar-19	Los Angeles, CA	Bird	1+0.15	1+0.29
Mar-19	Bloomington, IN	Bird	1+0.15	1+0.10
Mar-19	Charlottesville, VA	Bird	1+0.15	1+0.10
Mar-19	Columbia, SC	Bird	1+0.15	1+0.10
Mar-19	Baltimore, MD	Bird	1+0.15	1+0.29
Mar-19	Charlotte, NC	Bird	1+0.15	1+0.33
Mar-19	Detroit, MI	Bird	1+0.15	1+0.33
May-19	Santa Monica, CA	Bird	1+0.15	1+0.26
May-19	Santa Monica, CA	Lime	1+0.15	1+0.23
May-19	Santa Monica, CA	Jump	0+0.15	0+0.26
Jun-19	Seattle, WA	Jump	0+0.15	0+0.25
Jun-19	Seattle, WA	Lime	1+0.15	1+0.25
Jun-19	Austin, TX	Lime	1+0.15	1+0.25
Aug-19	Los Angeles, CA	Lime	1+0.15	1+0.23
Aug-19	Los Angeles, CA	Jump	1+0.15	1+0.26
Aug-19	Twin Cities, MN	Lime	1+0.15	0+0.20
Aug-19	Minneapolis, MN	Lime	1+0.15	1+0.20
Aug-19	St Paul, MN	Lime	1+0.15	1+0.20
Dec-20	Chicago, IL	Bird	1+0.37	
Dec-20	Chicago, IL	Lime	1+0.39	
Jan-22	Los Angeles, CA	Link	1+0.39	
July-23	Austin, TX	Bird	1+0.29	
Oct-24	San Francisco, CA	Spin	1+0.59	
Oct-24	San Francisco, CA	Lime	1+0.50	
Oct-24	Washington D.C.	Lime	1+0.32	
Oct-24	Washington D.C.	Spin	1+0.29	
May-25	Austin, TX	Lime	1 +0.39	

Table A.2: Referenced on page(s) 6, 15. The table reports the dockless mobility operators’ price updates. We collect this data from press articles. See, e.g., The Verge’s article “Riding Bird’s electric scooters just got more expensive in some cities” ([link](#)), Chicago, IL 2020 scooter pilot report ([link](#)), and operators’ pricing reports ([link](#)), ([link](#)), ([link](#)).

	Within 100 m of ride start location (scooters)			Daily fleet size (scooters)			Daily aggregate rides	Daily utilization (%)
	Spin	Bird	KC	Spin	Bird	KC		
min	1	0	0	0	0	0	1	0.000
25th percentile	8	21	0	56	0	159	137	0.356
median	16	44	0	173	609	159	274	0.832
75th percentile	36	84	2	544	964	159	750	1.835
max	210	414	12	1,200	1,450	159	4,805	6.873

Table A.3: Referenced on page(s) 11. Summary statistics from the raw data on the number of devices within 100 meters of ride start locations, daily fleet size, daily ridership, and daily scooter utilization across the entire service area, which spans 121 neighborhoods in Kansas City, MO.

	Within 100 m of ride start location (scooters)					Daily fleet size (scooters)			Daily aggregate rides	Daily utilization (%)
	Pct	Spin	Bird	KC	All	Spin	Bird	KC		
CBD Downtown	1	2	6	0	10	11	232	0	43	0.1
	25	8	39	0	52	42	324	8	105	0.4
	50	20	78	0	107	85	363	8	220	0.8
	75	50	127	3	183	123	394	8	438	1.9
	99	148	297	12	407	200	482	8	1,598	8.8
Crossroads	1	2	3	0	9	21	111	0	16	0.1
	25	8	18	0	35	44	171	5	65	0.4
	50	16	38	0	58	72	186	5	105	0.7
	75	29	62	0	91	102	214	5	221	1.4
	99	78	143	4	174	152	284	5	799	5.7
Crown Center	1	1	0	0	7	4	40	0	11	0.2
	25	6	15	0	30	17	62	3	31	0.6
	50	12	33	0	52	25	78	3	57	1.3
	75	21	60	4	80	44	93	3	116	2.5
	99	62	136	8	164	98	125	3	377	10.3
River Market	1	2	3	0	7	5	38	0	5	0.0
	25	8	16	0	32	22	58	4	22	0.3
	50	16	32	0	56	39	103	4	44	0.6
	75	32	60	0	83	62	143	4	96	1.5
	99	74	120	12	172	113	200	4	373	4.5
Old Westport	1	2	0	0	6	5	17	0	2	0.0
	25	9	8	0	24	18	24	5	15	0.3
	50	20	20	0	47	29	28	5	28	0.8
	75	47	33	0	76	60	31	5	54	1.6
	99	147	70	8	187	104	50	5	176	5.3
Columbus Park	1	2	3	0	8	3	14	0	1	0.0
	25	6	15	0	26	9	26	0	8	0.4
	50	12	27	0	39	16	36	0	23	1.1
	75	20	42	0	57	24	49	0	49	2.1
	99	38	82	0	110	33	73	0	181	8.0
West Plaza	1	1	3	0	5	1	18	0	1	0.0
	25	3	6	0	10	2	30	0	9	0.4
	50	4	15	0	20	4	34	0	19	0.9
	75	8	27	0	35	11	40	0	41	2.3
	99	16	56	0	58	19	49	0	110	7.5
Quality Hill	1	1	3	0	4	0	10	0	1	0.0
	25	3	9	0	14	2	23	0	6	0.2
	50	4	15	0	20	4	30	0	13	0.5
	75	9	24	0	40	6	37	0	25	1.2
	99	28	64	0	77	15	61	0	99	4.2
Hospital Hill	1	3	3	0	7	0	11	0	1	0.0
	25	9	12	0	27	9	20	1	7	0.2
	50	21	20	0	44	18	26	1	12	0.4
	75	34	34	0	67	22	36	1	28	1.0
	99	57	121	4	150	32	83	1	149	3.2
All	1	2	3	0	8	75	531	0	107	0.2
	25	8	21	0	36	165	778	26	282	0.4
	50	16	44	0	65	292	872	26	554	0.9
	75	36	84	2	117	432	1,016	26	1,030	1.7
	99	130	261	12	355	763	1,249	26	3,878	6.3

Table A.4: Summary statistics for the number of devices within 100 meters of a ride start location, daily fleet size, daily ridership, and daily scooter utilization in the nine highest-ridership neighborhoods of Kansas City, MO. (See Appendix C for data collection and handling.) The low utilization rates are robust to intra-day trends and finer spatial aggregation. Specifically, we: (i) split days into six time periods (9 a.m.–12 p.m.; 1 p.m.–4 p.m.; ... 1 a.m.–4 a.m.; and 5 a.m.–8 a.m.); (ii) divide Kansas City, MO into 50 blocks; and (iii) calculate average device utilization for each time period–block. Utilization is low across the board: the 50th, 75th, 90th, and 99th percentiles of utilization across time period–blocks are 0.10, 0.33, 1.04, and 3.66%, respectively.

	Median daily rides		Median daily fleet size (scooters)					
			Bird		Spin		Aggregate	
	weekend	weekday	weekend	weekday	weekend	weekday	weekend	weekday
CBD Downtown	533	198	376	359	91	85	464	454
Columbus Park	44	18	39	35	16	15	60	50
Crossroads	366	91	195	182	80	70	272	250
Crown Center	129	46	88	75	34	24	125	104
Hospital Hill	44	10	36	24	19	17	54	42
Old Westport	59	23	32	27	40	28	80	60
Quality Hill	17	12	34	28	5	3	39	32
River Market	103	38	110	92	46	38	161	135
West Plaza	46	17	36	33	5	3	42	36
All	1,277	452	970	839	334	289	1,337	1,126

Table A.5: Referenced on page(s) 16. The table reports the median of weekday and weekend daily rides and fleet sizes in the 9 neighborhoods of Kansas City, MO. To measure the elasticity of the aggregate fleet size with respect to aggregate demand we bootstrap the data 1,000 times by sampling dates with replacement. Then we calculate the median ratio of day-to-day relative change in fleet size over the day-to-day relative change in demand for each sample. We cannot reject the null that the average elasticity of the aggregate fleet size with respect to aggregate demand is 0 at the 5% level.

	Logit(Operator one is chosen)			
	(1)	(2)	(3)	(4)
Estimate ($\hat{\beta}$)	1.06***	0.36***	0.35***	0.34***
95% CI	(0.92, 1.16)	(0.26, 0.47)	(0.25, 0.48)	(0.25, 0.48)
Brand preference	No	Yes	Yes	Yes
Weekday FE	No	No	Yes	Yes
Temperature	No	No	No	Yes

Table A.6: Referenced on page(s) 22. This table reports rider choice parameter estimates under different model specifications. The unit of observation is a ride. “Brand preference” refers to adding an intercept to the model and “Temperature” refers to the average temperature on the date of the ride. *** $p < 0.01$.