# Optimal Local Transportation Pricing with Distributional Concerns

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## 1 Motivation and research questions

Individuals generate social costs in the form of pollution, greenhouse gas emissions, congestion, and other externalities when they travel locally. The magnitude of these externalities depends on whether they choose to travel by foot, bike, bus, car, or other transportation mode. In addition to correcting these externalities with a set of mode-specific Pigouvian taxes, a social planner might wish to consider the distributional consequences of these taxes if mode choice varies by travelers' characteristics. The interaction between these efficiency and equity concerns and the difficulty of measuring externalities makes setting optimal transportation taxes a challenging theoretical and empirical question.

Our proposed research considers this question in the context of shared scooters and bicycles ("micromobility" vehicles), which are a growing segment of the transportation market in the United States. In practice, users of these vehicles typically face higher per-mile taxes and fees than trips by motor vehicles (Thigpen, Fang, & MacArthur, 2023). The efficiency of these differential tax rates is unclear because the full extent of the externalities generated by micromobility trips is not well documented. The goal of this project is to estimate the optimal tax or subsidy for micromobility trips when accounting for their social cost compared with the social cost of travel via motor vehicles and public transit. We also consider how redistributive motives and constraints on policymakers' ability to tax different modes of transportation affects the optimal tax structure.

This paper makes both a theoretical and an empirical contribution to the literature on transportation and optimal taxation. In terms of theory, we characterize optimal micromobility pricing, using a sufficient-statistics approach to identify the parameters that govern the optimal price given distributional considerations and externalities. These parameters include price elasticities for micromobility use, switching or "mode-shift" elasticities between transportation modes, and the relationship between mode choice and riders' incomes and demographics. Intuitively, if shared e-scooter and bike trips frequently displace trips with higher social costs, the optimal transportation tax regime would involve a lower effective tax rate on micromobility vehicles than if they do so rarely. Similarly, the choice of which modes to tax, and how intensively to do so, depends on the price elasticity of demand for each mode because this elasticity determines how likely users are to switch away from that mode when taxed. Finally, if lower-income travelers tend to prefer some modes over others, the social planner may want to tax those modes less heavily than it would if concerned only about efficiency.

The paper's empirical contribution is to estimate the parameters of our theoretical model using trip-level microdata from the micromobility company Lime. The data describes a wide range of variation in prices and service provision that can be used to identify travelers' substitution patterns. By matching the data with income and demographic data on the areas where trips occur, we observe the association between traveler characteristics and mode choice.

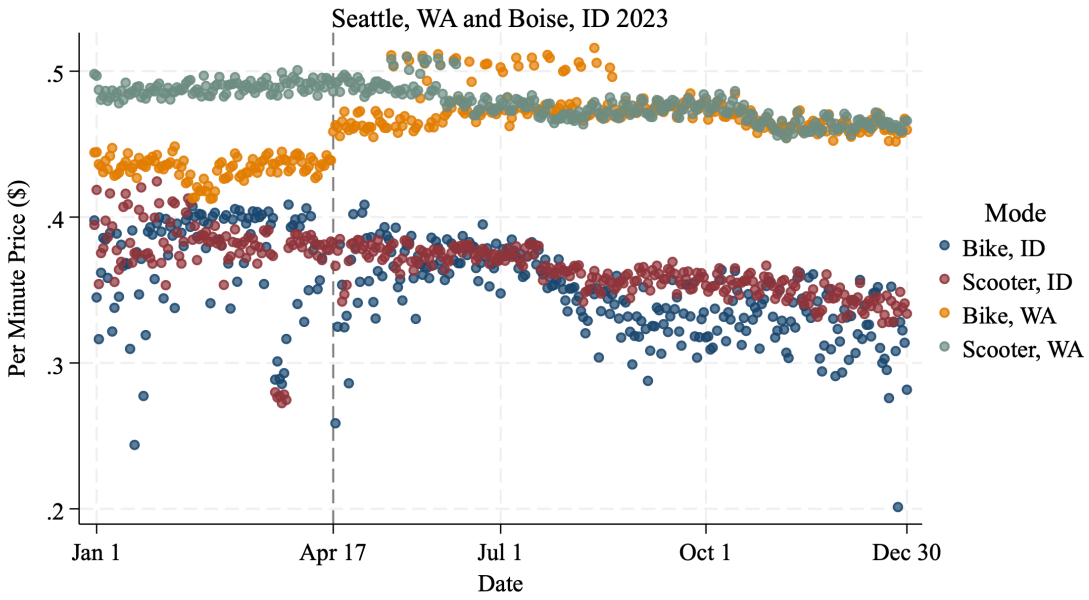
With estimates substitution patterns in hand and using externality costs from prior literature, we consider constrained-optimal taxes on micromobility travel. By contrast, the optimal fully-flexible tax would be individual-, mode-, and trip-specific, but such fine-grained policies are logistically impractical to implement and are often politically infeasible. We therefore consider simpler policies that can internalize a portion of the externality costs of transportation while meeting constraints such as budget balance and limits on mode-specific tax or subsidy rates. These may include mode-specific taxes on a per-trip basis, a fixed fee for participating in a particular market, or time-varying use fees.

## 2 Data

The key to our identification strategy is trip-level data from Lime, which operates e-scooter and bike share services in more than 50 U.S. cities. For each trip, these data describe the latitude and longitude of the start and end locations, the date and time that the trip started and ended, the price the traveler paid, the distance traveled, whether the device was an e-scooter or a bike, and a unique user identifier. The data shows spatial, temporal, and individual-level changes in pricing, as well as the geographic extent of service provision. Lime is working to provide internal documentation about the exact price changes and experiments that applied to dates, users, and geographic areas, but in the pilot data used in the results below we only observe prices paid.

Data on public transit, car travel, local congestion, and demographics come from a variety of sources. We use hourly traffic counts collected by the Federal Highway Administration (FHWA) and municipal governments to measure local car travel. Trip-level rideshare data from Uber and Lyft in New York City and Chicago supplement the traffic count data for these cities. Data on hourly traffic speeds and hourly public transit ridership from municipal transportation departments provide measures of congestion and public transit use. We use estimates from the literature to quantify externalities including the health effects of motor vehicle tailpipe emissions, greenhouse gas emissions from electric or combustion-powered transportation, roadway congestion, and injuries and fatalities from vehicle accidents. We use data from the U.C. Census' 2022 American Communities Survey (ACS) to measure income and demographics.

Figure 1: Daily average variable price ($/minute) by mode




## 3 Methods

We identify 3 types of parameters: (1) own-and cross-price demand elasticities for transportation using variation in micromobility trip prices, (2) mode-shift elasticities using extensive-margin variation in the availability of micromobility vehicles, and (3) the association between mode choice, income, and demographics.

**1. Demand elasticities.** Lime has varied the price of bike and scooter trips over time and across markets through user-level and city-wide experiments and promotions, and in response to regulation by local governments. An example of this price variation is illustrated in Figure 1, which shows the variable price ($/minute) charged to users of e-scooters and bikes over time in two cities: Seattle, Washington and Boise, Idaho. This variation allows for a variety of strategies to identify price elasticities; to illustrate possible approaches, our preliminary results use one source of price variation in Seattle to estimate own-price elasticities for bikes. On April 17, 2023 (indicated by a vertical, dashed line in Figure 1), the company raised prices for bikes in Seattle by about $0.02/minute.

**2. Mode-shift elasticities.** Since Lime has expanded its operations rapidly and the regulatory environment for its operations in many cities has changed over time, travelers in many cities and neighborhoods abruptly gained or lost access to the company's e-scooters and bikes in the sample period. We use a staggered difference-in-differences (DiD) design to estimate mode-shift elasticities using these changes in the supply of micromobility vehicles. For location $i$ at time $t$, the baseline specification is:

$$y_{it} = \alpha_i + \gamma_t + D_{it} + \epsilon_{it} \tag{1}$$

where $y_{it}$ is a measure of vehicle counts or traffic speed; $\alpha_i$ and $\gamma_t$ are location and time fixed effects, and $D_{it}$ is an indicator equal to one when micromobility vehicles suddenly become accessible/inaccessible in location $i$. Rescaling outcomes by the change in micromobility usage or embedding the DiD design in instrumental variables framework yields mode shift elasticities.

**3. Income and demographic associations.** We do not observe income and demographic information for individual users of Lime vehicles, so we match trips taken by micromobility vehicles as well as by public transit, rideshare, and private vehicles with demographic information from the ACS based on the census block group where trips begin, end, and pass through. This allows us to calculate the income and demographic shares of users on each transit mode.

# 4 Preliminary results

## 4.1 Demand elasticities

We compare the change in micromobility usage within Seattle before and after the price treatment in a window around the date of the price change. This is functionally a regression discontinuity estimation strategy in which time is the running variable. The regression specification is:

$$y_{it} = \delta f(Date_t) + \beta Post_t + \gamma_t + \epsilon_{it} \tag{2}$$

where $f(Date_t)$ is a smooth function of date, $Post_t$ is a binary variable equal to one in periods after the price change occurs, and $\gamma_t$ is a set of time fixed effects, which are hour of day and day of week in our preferred specification. Outcome $y_{it}$ is the natural log of variable price in a spatial grid cell $i$ in hour $t$ in the first stage and the natural log of the number of trips beginning in a grid cell and hour in the reduced form. $\beta$ is the coefficient of interest. We present results using a linear trend in date and a symmetric 28-day window around the pricing event in Table 1. The results from a number of alternative specifications are similar in magnitude, subject to statistical power requirements.

**Table 1: Own-price elasticities using within-city variation**

| | First stage | | Reduced form | | IV | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | ln(price) | ln(price) | ln(trips) | ln(trips) | ln(trips) | ln(trips) |
| Post 4/17 | 0.053* | 0.054* | -0.015 | -0.013* | | |
| | (0.004) | (0.003) | (0.002) | (0.001) | | |
| ln(price/min) | | | | | -0.334* | -0.290 |
| | | | | | (0.157) | (0.151) |
| Date | 0.001 | 0.001 | 0.003** | 0.003* | 0.003*** | 0.003*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) | (0.001) |
| Hr of day FE | No | Yes | No | Yes | No | Yes |
| Day of week FE | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 32,823 | 32,823 | 32,823 | 32,823 | 32,823 | 32,823 |

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The first two columns of Table 1 provide an estimate of the magnitude of the pricing change shown in Figure 1. The coefficient on "Post 4/17" in column (2), our preferred specification, indicates that the price increase for bikes on April 17 was about 5.4% ($\sim$ 2 cents on a base of \$0.47). The reduced form in columns (2) and (3)

shows the effect of the price change on the log of hourly trips within a spatial grid cell. The coefficient on "Post 4/17" in column (4) suggests that the 5.4% increase in price on April 17 corresponded to a 1.3% reduction in bike trips. Columns (5) and (6) present the results from an IV regression that scales the reduced form coefficient by the size of the first stage price change using a two-stage least squares regression. Our preferred elasticity estimate, in column (6), suggests that a 1% increase in the price per minute of bike rides results in a 0.29% decrease in bike rides taken.

This estimate suggests that micromobility users' demand is more inelastic than estimates from prior studies on micromobility use that use survey-based or simulated measures of demand, which range from -1.94 to -5.0 for bicycles (Kaviti & Venigalla 2019; Manout et al. 2023). To our knowledge, our study would be the first to calculate demand elasticities for micromobility vehicles using data on realized consumer decisions. Notably, our estimates are similar to estimates of elasticities for public transit fares that use trip-level microdata and an observational research design. For example, Kholodov et al. (2021) find an elasticity of -0.46 for riders on the Stockholm metro, and Wang et al. (2018), who find an elasticity of -0.316 for riders on the Beijing metro.

## 4.2 Income associations

Table 2 shows the relationship between the natural log of trips in a day that begin in a given census block group and income and demographic characteristics of that census block group from the ACS. We code the racial categories such that each is between 0 and 100 and indicates the percent of residents of a given race in the census block group where the ride starts. Income is measured as the natural log of the median income in the census block group. We measure the number of trips beginning within a census block group separately for users enrolled and not enrolled in a program called Lime Access. This is an affordability program that, in Seattle, provides reduced-fare rides to individuals for are enrolled in a means-tested federal program such as SNAP or Medicaid.

**Table 2: Association between trips and demographics**

| | Means-tested discount riders | | | Full-price riders | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | ln(trips) | ln(trips) | ln(trips) | ln(trips) | ln(trips) | ln(trips) |
| ln(median income) | | -0.243*** | -0.684*** | | -0.431*** | -0.409*** |
| | | (0.005) | (0.026) | | (0.005) | (0.005) |
| % White | -0.006*** | | -0.001 | -0.004*** | | -0.001* |
| | (0.001) | | (0.001) | (0.000) | | (0.000) |
| % Black | 0.018*** | | 0.012*** | -0.005*** | | -0.010*** |
| | (0.002) | | (0.002) | (0.000) | | (0.000) |
| % Asian | 0.023*** | | 0.025*** | 0.019*** | | 0.020*** |
| | (0.001) | | (0.001) | (0.000) | | (0.000) |
| % Other Race | 0.000 | | -0.007** | -0.015*** | | -0.021*** |
| | (0.002) | | (0.002) | (0.001) | | (0.001) |
| N | 122,423 | 113,971 | 113,971 | 261,199 | 247,511 | 247,511 |

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Regressions of rides taken by Lime Access users on the income and demographics of the census block groups where these rides originate are presented in columns (1) - (3). As expected, Lime Access users are more likely to begin their rides areas with higher shares of low-income and black residents. Column (3) suggests that conditional on income, a 1 percentage-point increase in the share of black residents in a census block group is associated with a 1.8% increase in Lime Access rides originating in that block group. Conditional on race, a 1 percent increase in the income of residents in a census block group is associated with 0.2% fewer Lime Access rides. Remarkably, the negative association between rides and both income and the share of white residents holds for riders who are not in the Lime Access program, as shown in columns (4) - (6). In short, low-income and minority communities within Seattle appear to have more Lime riders. This suggests that the status quo tax regime in which travel by these vehicles is more heavily taxed than travel by cars may be regressive.

# 5 Relevance to the Department of Transportation (DOT)

The growing use of micromobility vehicles has implications for transportation policy throughout U.S. cities, which currently lacks a coherent and unified approach. Electric bikes and scooters bring new challenges and opportunities in terms of safety; docking and parking; the design of sidewalk, bike lane, and road infrastructure; and possible reductions in air pollution and carbon emissions. By measuring social costs and benefits associated with micromobility vehicles, the proposed work can inform the DOT about what information and guidance guidance to offer to local jurisdictions to improve their transportation tax and pricing policies.

# 6 Research team

**Benjamin Lockwood** is an Assistant Professor of Business Economics and Public Policy at the University of Pennsylvania Wharton School. His past research studies optimal taxation in settings where policymakers care both about reducing inequality and about encouraging or discouraging certain activities. He has published studies on the optimal taxation of soda, state-run lotteries, and work subsidies in journals such as the Quarterly Journal of Economics and the Review of Economic Studies.

**Peter Lugthart** is a PhD student in the Business Economics and Public Policy department at the University of Pennsylvania Wharton School. His prior and ongoing research has focused on how individuals respond to taxation and regulation of externalities in contexts including land use and housing markets.

**Arthur van Benthem** is an Associate Professor of Business Economics and Public Policy at the University of Pennsylvania Wharton School. He specializes in environmental and transportation economics using tools from public finance. His related work includes studies of vehicle tailpipe emissions regulation, the efficiency costs of imperfect externality pricing, and optimal highway speed limits in journals including the Quarterly Journal of Economics and The Journal of Political Economy.

# 7 Conflicts of interest

All authors declare that they have no conflicts of interest relevant to the work described in this proposal.

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