Micromobility and Safety

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Introduction

Across cities in the United States, transportation is dominated by the automobile. The many negative externalities generated by automobiles have been well documented, yet remain an outsized problem in urban environments. For one, traffic fatalities represent approximately 1.3% of all deaths in the United States, many of which are preventable. According to the Fatality Analysis Reporting System, in 2022, there were almost 43,000 traffic fatalities across the country, representing a nearly 20% increase relative to the total in 2019.

Recent technological innovations in transportation have provided individuals with alternatives to reduce vehicle dependency. The biggest example of this is the introduction of rideshare (e.g., Uber and Lyft) throughout the 2010s. In one study, Hall et al. (2018) demonstrated the complementarity between public transportation and Uber, suggesting that individuals could use rideshare as a first/last mile solution to the fixed route and scheduled nature of public transportation. Even more recently, micromobility options such as bikes and scooters have spread to small and large cities alike. According to the Bureau of Transportation Statistics, micromobility options currently exist in over 350 cities across the United States. In these cities, it is often less costly, both financially and temporally, to find a bike or scooter along one's route than to order an Uber or Lyft. Therefore, it is possible that micromobility could supplant rideshare as a first/last mile solution for commuters in urban environments given its relative affordability and accessibility.

A second strand of literature has shown that the introduction of rideshare reduces both instances of driving under the influence (DUIs) as well as alcohol-related driving fatalities (Dills and Mulholland, 2018; Anderson and Davis, 2021; Lennon et al., 2024). Choosing rideshare over driving enables impaired individuals to effectively eliminate the risks they impose on others and themselves. However, the safety implications are less clear if these individuals instead elect for micromobility. Unlike rideshare, choosing micromobility does not reduce the number of impaired drivers, it only changes the types of vehicles operated. It has been shown that traffic composition has important implications for safety outcomes (Wen et al., 2018).

In this study, we explore how the introduction of micromobility impacts health and safety. First, we hypothesize that, like rideshare, micromobility could provide an alternative to driving (an automobile) under the influence. As a first step, we examine how DUI arrests respond to the introduction of micromobility in a city. Though as mentioned above, unlike rideshare, a reduction in DUIs attributable to micromobility does not necessarily point to safer roads. To address this concern, we would like to examine data from the Healthcare Cost & Utilization Project (HCUP). We are interested in exploring injuries due to falls or collisions, which we could observe at the hospital level. This would provide a more accurate and detailed understanding of the safety implications associated with micromobility.

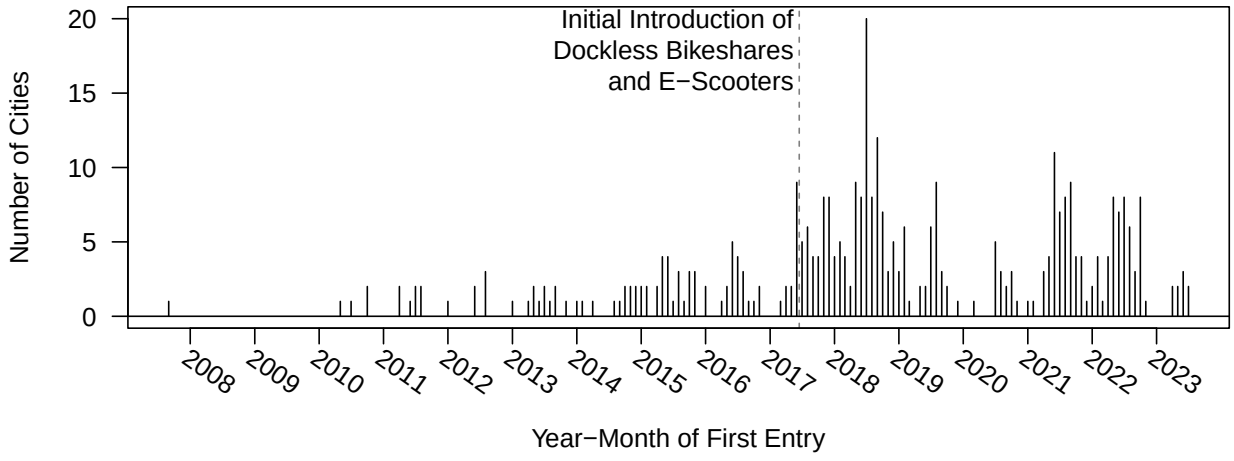
In the rest of this proposal, we present our preliminary, proof-of-concept findings for DUIs and detail the contribution to the literature. We are seeking funding to facilitate efforts to collect data containing health and safety information. In particular, we believe that the NBER's HCUP data use agreement could be a potential solution. With these data, we could paint a more complete picture of the safety implications of this transportation technology to inform local and national policy.

Data and Empirical Setting

The Bureau of Transportation Statistics (BTS) has released city-by-year micromobility information, including the entry and exit months for docked, dockless, and e-scooter systems in the United States. According to the data, the first docked bikeshare system was installed in Tulsa, Oklahoma in August 2007. From August 2007 and the opening of the first dockless system, 100 docked bikeshare systems opened up across the country. The first dockless bikeshare systems were launched nearly ten years later in June 2017 in Dallas (TX), Fort Worth (TX), and Key Biscayne (FL), while the first e-scooter system was launched in September 2017 in Santa Monica (CA). Between then and 2020, 68 cities obtained a dockless bikeshare system, 74 obtained e-scooters, and 42 got both. During and following the pandemic, 16 got dockless bikeshare, 124 cities got e-scooters, and 14 got both.

As recently as June 2023, BTS data notes that e-scooters were introduced to 254 cities, dockless bikeshare has been introduced to 140, and docked bikeshare to 142. As a note, these numbers do not account for systems that have been removed.Figure 1 below displays the distribution of dates where the first micromobility option was installed in each of the 386 cities in the BTS data.

Figure 1: Timing of Each City's First Micromobility Option



We also collected data from the Federal Bureau of Investigation's Crime Data Explorer. These data include agency-by-month counts of arrests for particular crimes, including DUIs. We hand-matched agencies to cities with micromobility in the BTS data. Within these data, we focus on driving under the influence arrests, which acts as a proxy for drunk driving. We use data from 268 agency/city matches between the years 2010 and 2019. Over this period, 30% of agencies got docked bikeshare, 27.6% got dockless bikeshare, and 29.1% got e-scooters.

Our empirical strategy closely follows the literature on the rollout of Uber. We use a staggered difference-in-differences research design to control for unobservable confounding factors. We estimate models of DUI arrests for agency a in time period t using the following baseline specification:

$$Y_{at} = \delta M_{at} + X_{at}\beta + \alpha_a + \tau_t + \epsilon_{at} \tag{1}$$

where M_{at} is a binary variable equal to one if micromobility has been introduced to agency a's city in time t, making δ our parameter of interest. X is a matrix of time-varying controls including median income, median age, percentage of the population that identifies as white, percent of the population that has at least a bachelor's degree, and whether Uber has a presence. Finally, in this specification, α_a and τ_t represent the (potentially problematic) two-way fixed effects. We estimate models where Y is either the count of DUI arrests (with OLS and Poisson), the inverse hyperbolic sine of DUI arrests, or the inverse hyperbolic sine of per-capita DUI arrests. While we are interested in point estimates, we think event study figures give us a better understanding of the setting dynamics. We have chosen to omit point estimate results due to the space constraints of this proposal.

The estimated coefficients across the different specifications all point to the introduction of micromobility reducing DUI arrests, with the largest magnitude coming approximately a year after their introduction. This makes sense, as riders need time to familiarize themselves with the new technology. In some specifications, we even find a slight "bounce-back" effect where the coefficients trend back toward zero from months 15 to 24. This could be due to a variety of reasons ranging from social (e.g. the novelty of micromobility wearing off) to juridical (changing DUI laws/enforcement to focus more on micromobility).

Of course, due to the recent difference-in-differences literature, we know that biases may arise when estimating models using two-way fixed effects and staggered treatment timing, especially when the treatment effect is heterogeneous and dynamic. Indeed, when we estimate a Goodman-Bacon decomposition, we find evidence of bias in our coefficients albeit only to a small degree. We find that the "forbidden" comparison only accounts for about 8% of our estimated parameter, but the effect is positive and relatively large. To address this, we apply novel estimators that account for these biases. Dube et al. (2023) recommend a local projections approach to difference in differences (LP-DiD), where the model is only estimated for newly treated observations and what the authors call "clean" controls: never- and not-yet-treated units. We estimate the following equation:

$$\text{DUI}_{a,t+h} - \text{DUI}_{a,t-1} = \delta_h^{LP}\Delta M_{a,t} + X_{at}\beta^h + \tau_t^h + e_{at}^h \tag{2}$$

using only observations where $\Delta M_{at} = 1$ (newly treated) or $M_{a,t+h} = 0$ (clean control). This is akin to the "stacking" estimator in Cengiz et al. (2019) and Wing et al. (2024). In Figure 2, we plot the event study coefficients generated by this estimator when the outcome is the count of DUI arrests for agency a in time period t, h months since micromobility was introduced to the city. Ultimately, we find qualitatively similar results to our initial two-way fixed effect estimations.

Figure 2: Effect of Micromobility on Arrests for Driving Under the Influence

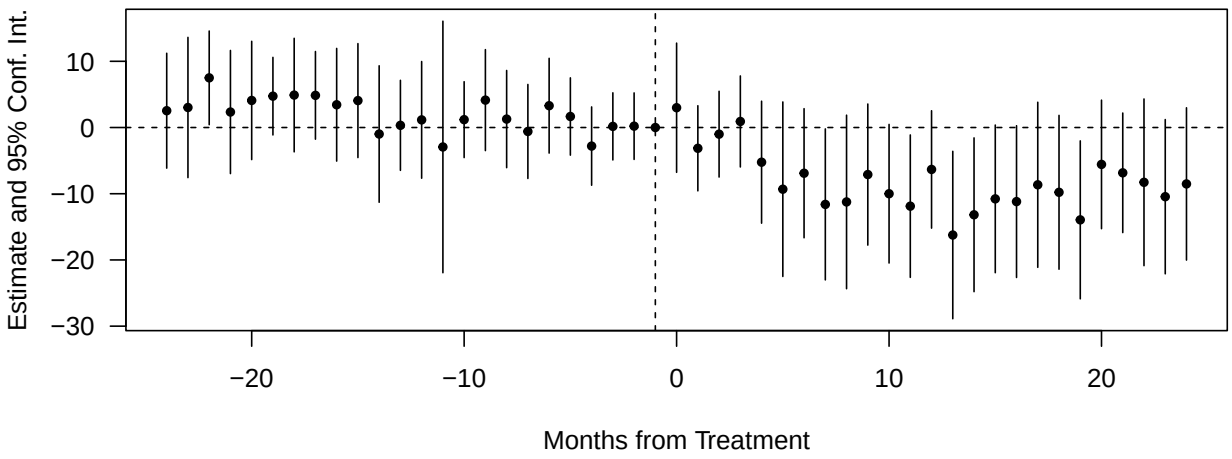


Figure 2 shows a reduction of about 10 DUIs per month, amounting to a $\approx 10\%$ reduction. While this may seem like an attractive headline on the surface, we hesitate to interpret this as a reduction in a negative externality. Using HCUP's injury data, we would be able to fully examine the safety implications of the introduction of micromobility.

Existing Literature and Contribution

There are many ways micromobility may affect the world such as congestion and vehicle emissions. For example, Asensio et al. (2022) examined the effects of a micromobility ban on congestion in Atlanta, and found a significant increase in travel times and congestion after these bans took effect. This study highlights the importance of constructing effective policy around micromobility. Another aspect of first-order importance is health and safety. Given the rapid expansion of micromobility across the United States, it is important to understand the implications of these new networks. However, little economic research has been done on micromobility. To our knowledge, Button et al. (2020) is the only paper published in an economics journal focusing specifically on micromobility.

There is, however, some work pointing to the health and safety implications of micromobility. Tark (2023) estimated 360,800 micromobility-related emergency department visits from 2017 through 2022, 47% of which involved an e-scooter. However, visits were not uniformly distributed across time. The Consumer Product Safety Commission estimated an increase in emergency department visits of about 270% from 2017 to 2022. Shichman et al. (2022) shows that, for a particular emergency department in Israel, nearly 80% of e-scooter-related injuries were due to falls rather than collisions. This evidence highlights the need for more research on health and safety, particularly outside of motor vehicle crash outcomes.

Composition of Research Team

Margaret Bock is an Assistant Professor of Economics at Goucher College in Baltimore, Maryland. She studies transportation infrastructure through the lenses of urban economics and public finance. Alexander Cardazzi is an Assistant Professor of Economics at Old Do-

minion University in Norfolk, Virginia. He studies urban economics broadly with a particular interest in transportation externalities.

The authors were recipients of this grant in 2019 as graduate students. They could not present that research project in person (only virtually) due to the COVID-19 pandemic. In addition to obtaining funding for a project analyzing the frontier of personal transportation technology, both researchers would benefit from the opportunity to network with those at the NBER and DOT in person. Both authors are eligible to be paid as NBER employees.

Conflict of Interest Statement

There is no conflict of interest. We do not work for anything related to the transportation industry.

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