Ridesharing and Substance Use Disorder Treatment*

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Abstract

We examine whether ridesharing provides a meaningful transportation alternative for those who require ongoing healthcare. Specifically, we combine variation in UberX entry across the U.S. with the Treatment Episode Data Set to estimate the effect of ridesharing on admissions to substance use disorder treatment. People needing such treatment report transportation as a barrier to receiving care. We find that UberX entry into a core-based statistical area has no effect on the overall number of treatment admissions. However, we find a decline in non-intensive outpatient treatment which is fully offset by an increase in intensive outpatient treatment. Given the required relative frequency of non-intensive and intensive outpatient treatment in terms of visits per week, our findings indicate that UberX helps to reduce transportation barriers to accessing appropriate healthcare. We support a causal interpretation for our findings using event studies to show parallel trends in our outcomes before the arrival of UberX, a variety of heterogeneity analyses and robustness checks, and by using difference-in-differences estimators that are robust to treatment effect heterogeneity and dynamics.

Keywords: Uber, Transportation Barriers, Health Care Access, Substance Use
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1 Introduction

The emergence of ridesharing has led to significant changes in how people access and use transportation (Hall et al., 2018; Tarduno, 2021; Agrawal and Zhao, 2023). Because of convenient features such as on-demand booking, accurate location sharing, and digital payments, ridesharing services are often seen as more convenient than traditional taxi services. One important area where ridesharing may relax existing transportation constraints is in accessing healthcare. Indeed, the advent of UberHealth suggests that healthcare providers often use ridesharing services to help transport patients to and from appointments. According to UberHealth, introduced to U.S. markets in 2018, the UberHealth platform helps improve patient care by enabling healthcare organizations to arrange rides and services on behalf of others by using a centralized, easy-to-use dashboard or an application programming interface.[1]

We examine whether ridesharing affects access to a category of healthcare that requires relatively frequent and ongoing engagement: treatment for substance use disorders. This treatment context is particularly useful to study, as individuals in need of substance use disorder treatment often face transportation barriers preventing them from obtaining their preferred level of care – see, e.g., O'Brien et al. (2019) and Harwerth et al. (2023).[2] Remaining in treatment is crucial for patients, as dropping out of treatment is associated with elevated risk of a fatal overdose (Zanis and Woody, 1998). Moreover, there is substantial unmet need for substance use disorder treatment in the United States. Only 12% of people with a substance use disorder receive care each year (U.S. Department of Health and Human Services, 2020) and, among those that receive care, many patient report that they do not receive sufficient care (Substance Abuse and Mental Health Services Administration, 2023). Given the social costs of substance use disorder, estimated to be $682 billion per year (Caulkins

[1]See uberhealth.com for more information. Website last accessed 2/16/2024.

[2]Harwerth et al. (2023) provide an overview of 18 studies that identify various transportation-related barriers to outpatient substance use treatment, including public transit availability, lack of a driver's license, and high transportation costs.

et al., 2014),[3] and the effectiveness of treatment (see Section 2), quantifying any changes in treatment uptake is an important part of assessing the overall societal benefits of ridesharing.

To estimate the impact of ridesharing on substance use disorder treatment utilization, we use the Treatment Episode Data Set (TEDS) for the years 2008 to 2018 to study how UberX, Uber's taxi-like service, has affected substance use disorder treatment admissions. The TEDS is a national database of two million admissions to specialty substance use disorder treatment centers each year. Admissions are parsed by treatment modality (i.e., residential or hospital, detoxification, intensive outpatient, and non-intensive outpatient), which allows us to study admissions both overall and across treatment modalities with very different requirements for patient transportation to and from the center.[4] We are particularly interested in whether ridesharing allows patients to pursue more frequent intensive outpatient treatment (three or more sessions per week) rather than non-intensive outpatient treatment when transportation-related barriers are relaxed. In contrast, we would expect transportation availability to have less impact on detoxification or residential treatment admissions, as these settings do not require regular transport to and from the center.

To identify the effects of ridesharing on substance use disorder treatment admissions, we leverage spatial and temporal variation in UberX entry across U.S. Core Based Statistical Areas (CBSAs) starting with New York City in 2012 and then 261 additional cities by the end of 2018. We support a causal interpretation of our findings using event-study and difference-in-differences approaches that are robust to treatment effect heterogeneity and dynamics (i.e., the two-stage difference-in-differences imputation estimator proposed by Gardner, 2022).

Our central estimates suggest that UberX entry has no observable effect on the total number of substance use treatment admissions in a CBSA. However, the null result on total admissions masks interesting and clinically-relevant changes in patterns of treatment received

[3]Inflated by the authors from the original estimate ($481 billion in 2011 dollars, see Figure 1 in Caulkins et al., 2014) to 2024 dollars using the Consumer Price Index - Urban Consumers.

[4]We discuss these modalities in greater detail in Section 3.

by patients with substance use disorder. We find significant changes in the *type* of care received by patients, estimating a reduction of 0.54 non-intensive outpatient admissions per 1,000 residents (24.4%) following UberX entry in a CBSA. This decline is fully offset by an increase of 0.68 intensive outpatient admissions per 1,000 residents, suggesting substitution from less to more transportation-intensive treatment post-UberX entry. As expected, we do not find evidence that UberX entry meaningfully impacts admissions to detoxification or residential treatment, settings with lower transportation requirements. Our findings suggest that ridesharing allows patients to receive more intensive outpatient care, potentially reflecting a better matching of patients to treatment.

Primarily, we see the effects concentrated among patients 18-34 years old. Smith (2016) report that young adults were the most frequent users of ridesharing services (as of early 2016) with 10% of those aged 18-29 living in urban areas reporting using these services weekly. In contrast, Smith reports fewer than 1% of people over 50 used ridesharing weekly, while those over 50 comprise 14% of all TEDS admissions. The fact that we see stronger effects in settings with the highest transportation demands and among those most likely to use UberX during the sample period supports a causal interpretation of our findings. Further, we find that the largest impacts on outpatient care occur in areas where (a) public transit options are weaker, (b) there are fewer treatment centers per capita, and (c) Medicaid eligibility was not expanded under the Affordable Care Act.[5] These patterns again support the idea that our findings are related to a significant change in transportation access among people seeking substance use disorder treatment. We show that our estimates are robust to a variety of alternate specifications and sample restrictions. Moreover, we present event studies that provide evidence supporting the parallel trends assumption, and show that the treatment effects increase over time following UberX entry, a pattern that is consistent with the UberX

[5]Medicaid is the largest purchaser of substance use disorder treatment in the country (Substance Abuse and Mental Health Services Administration, 2014).

market growing as more riders and drivers use the platform (Bagchi, 2018; Hall and Krueger, 2018; Hall et al., 2018).

Our work connects to at least two strands of economic literature. First, we make several contributions to the existing literature on the impact of ridesharing. For example, Moskatel and Slusky (2019) show that ridesharing services are used as an alternative to ambulances. Our findings provide further evidence that ridesharing can reduce transportation barriers and improve access to healthcare. Our work also shows that UberX can help individuals receive their preferred treatment for substance use disorders, which is of critical importance given that ridesharing has also been shown to increase alcohol consumption (Zhou, 2020; Teltser et al., 2021). More broadly, our work adds to society's understanding of the transformative effects of ridesharing on communities, where the existing literature has also uncovered significant impacts on labor markets (Berger et al., 2018; Chen et al., 2019), public transit usage and congestion (Hall et al., 2018; Tarduno, 2021; Agrawal and Zhao, 2023), crime (Dills and Mulholland, 2018), and traffic fatalities and drunk driving (Brazil and Kirk, 2016; Greenwood and Wattal, 2017; Anderson and Davis, 2021; Barrios et al., 2022).

Second, we shed new light on an important barrier to substance use disorder treatment: transportation. A large literature explores factors that impact treatment utilization for these disorders, such as health insurance coverage (Meinhofer and Witman, 2018; Saloner et al., 2018). Our work shows that improving transportation options can facilitate treatment uptake including treatment that may be better-matched to patient need. Beardsley et al. (2003) and Amiri et al. (2018) demonstrate that proximity to care is critical for treatment compliance. Corredor-Waldron and Currie (2022) examine the impact of treatment center openings and closures on substance use disorder-related outcomes. They find a 7.4% increase in drug-related emergency department visits after a treatment center closure and a 6.5% decrease when a center opens. Their findings suggest that expanding access to treatment leads to significant improvements in drug-related morbidity. Looking at mortality, several studies show that increases in the number of treatment centers per county reduces fatal drug overdoses and alcohol poisonings (Swensen, 2015; Bondurant et al., 2018; Bradford and Maclean, 2024; Deza et al., 2023). For example, Swensen (2015) finds that a 10% increase in treatment centers in a county reduces drug-induced mortality by 2%. The literature suggests that ridesharing should increase the private and social benefits associated with substance use treatment (Koenig et al., 2000; Daley et al., 2001).

From a policy perspective, some states and localities are experimenting with using UberX or other ridesharing services as a means to support patients receiving substance use disorder treatment.[6] These interventions include full or partial funding to patients for ridesharing. Our work — which shows that UberX entry allows patients to receive care that is more "transportation-intensive" — suggests that these interventions may have important benefits for patients and their communities.

In summary, our work contributes to the literatures on ridesharing and healthcare utilization by providing novel evidence on how ridesharing can affect treatment for substance use disorder. Section 2 provides a discussion of substance use disorders and treatment in the U.S. In Section 3, we summarize the TEDS data and describe our approach to estimation. We present our main findings in Section 4. We offer concluding remarks in Section 5.

2 Substance Use Disorder and Associated Treatment

Addiction experts state that substance use disorders occur "...when the recurrent use of alcohol and/or drugs causes clinically and functionally significant impairment, such as health problems, disability, and failure to meet major responsibilities at work, school, or home" (American Psychiatric Association, 2013). Substance use disorders often emerge in young

[6] Please see https://www.ideastream.org/health-science/2018-04-30/hospital-using-uber-and-lyft-to-transport-patients-to-drug-treatment, https://www.narconon-suncoast.org/blog/uber-pilot-program-offers-free-rides-to-rehab.html, and https://www.wboy.com/news/west-virginia/justice-announces-program-that-will-pay-you-to-drive-others-to-substance-recovery/. All websites last accessed 2/16/2024.

adulthood (Kessler et al., 2005), likely from a combination of environment and genetics. These disorders negatively impact health, employment, and other socioeconomic outcomes.

Unfortunately, the U.S. is currently in the midst of a substance use disorder crisis, closely related to the use of opioids (Maclean et al., 2022). In 2021, there were over 106,000 drug-related fatal overdoses, an increase of over 530% compared to 1999 (16,849) (National Institute on Drug Abuse, 2023), and 17.5% of Americans 18 years and older (44.4 million) had a substance use disorder in 2022 (Substance Abuse and Mental Health Services Administration, 2023). The costs of substance use disorder extend beyond the individual with a disorder and impact society through reduced labor market productivity, increased healthcare costs, and crime.[7] As noted in Section 1, the costs to the U.S. of substance use disorder are estimated to be $682 billion per year (Caulkins et al., 2014).

While substance use disorder is a devastating medical condition, there are a range of options for prospective patients (Deza et al., 2022). Patients can receive care in private clinician offices (e.g., psychiatrists, psychologists), specialized centers (outpatient or residential), crisis centers, or hospitals (e.g., specialty units in community hospitals or psychiatric hospitals).[8] Some patients can receive treatment through their primary care provider while others use informal care such as Alcoholics Anonymous, Narcotics Anonymous, or in religious settings. Formal treatment often includes counseling (individual, family, or group) and/or medication management, with the frequency and/or duration of treatment varying across settings. A feature of substance use disorder treatment that is distinct from general healthcare is the provision of "wrap-around" services. Wrap-around services include treatments that are designed to improve social functioning of patients and help them re-integrate into society (Evans et al., 2023), as patients with substance use disorders can face challenges in other

[7]The existence of internalities suggest that the personal costs of substance use disorder may not be fully incorporated into decision making by the afflicted person (Gruber and Köszegi, 2001).

[8]Substance use disorders are generally viewed as chronic conditions. Thus, a patient may not be "cured" after receiving treatment, but treatment can allow for improved management of the disorder.

spheres of their lives. While these services vary across treatment centers, they can include education and vocational programming, social skills development, financial planning, legal advocacy, and assistance with access to social services.

We focus on treatment received in specialized outpatient and residential substance use disorder treatment centers. Care in these settings represented 37% of total U.S. spending on substance use disorder treatment ($15.5 billion) in 2020 (Substance Abuse and Mental Health Services Administration, 2014). In 2022, 4.6 million Americans 12 years and older received at least one episode of substance use disorder treatment in these settings (Substance Abuse and Mental Health Services Administration, 2023), reflecting 42% of formal care for substance use disorder in that year.[9] While the modalities we consider do not include all treatment available to patients, they capture modalities that are effective (Lu and McGuire, 2002; Stewart et al., 2002; Gossop et al., 2003; Reuter and Pollack, 2006; McCollister et al., 2013; Popovici and French, 2013; McCarty et al., 2014) and are recognized as part of the continuum of care supported by addiction experts (Mee-Lee et al., 2013).

3 Data and Estimation

3.1 Data

We use data on substance use disorder treatment admissions from the TEDS. Every year, TEDS gathers information from specialized substance use treatment centers across the country. TEDS captures information about those aged 12 or older receiving treatment for substance use disorder. There is mandatory reporting for centers receiving federal public funding, including data on both publicly and privately supported patients. In some states, centers without federal public funding must also report (e.g., Medicaid certified centers).[10]

[9] Formal care is defined by the authors in this calculation as care not received in jail/prison, an emergency department, or a self-help group.

[10] See https://www.icpsr.umich.edu/web/ICPSR/series/56, website last accessed 4/26/2024.

Patient-level data are collected at admission and include demographics (e.g., age, sex), setting (e.g., residential, detoxification), referral source (e.g., self, criminal justice system), treatment planning (e.g., medication), and information on substances of use (e.g., alcohol, opioids, route of administration). Centers provide this information to state substance use disorder agencies that harmonize data and report to TEDS. Appendix Table A1 provides demographics of patients receiving care in TEDS-tracked centers over our study period (2008-2018), dropping admissions outside the CBSAs included in our analysis (described in Section 3). Overall, we see that patients admitted to TEDS-tracked centers are younger and observably less advantaged than the general U.S. population.

Our main outcomes of interest are total, detoxification, residential, intensive outpatient, and non-intensive outpatient admissions per 1,000 population in each CBSA. Naturally, total admissions is the sum of detoxification, residential, intensive outpatient, and non-intensive outpatient admissions. Appendix Figure A1 presents trends in substance use treatment admissions 2008-2018. Overall, we see a small decline in total and non-intensive admissions between 2008 and 2015, with a modest increase in the final years of the study period. The other three categories are relatively flat. As evident in Appendix Figure A1, non-intensive outpatient is by far the most common modality observed in the data.

Per the Substance Abuse and Mental Health Services Administration (SAMHSA), detoxification treatment is a set of interventions aimed at managing acute intoxication and withdrawal (Substance Abuse and Mental Health Services Administration, 2006). Other types of admissions involve ongoing treatment for substance use disorders. For example, a residential stay, which can last from 30 to 90 days, involves non-acute care in a setting with treatment services for alcohol and other drug use. In this type of treatment, the patient is generally on the premises 24 hours per day (Substance Abuse and Mental Health Services Administration, 2022). We combine residential admissions with hospitalizations, which involves a patient receiving treatment on an inpatient basis in a psychiatric unit in a community hospital or a psychiatric hospital as described in Section 2, since hospitalization care is quite rare in the U.S. during our study period.[11] Outpatient programs offer an alternative to residential treatment. These programs often focus on relapse management and are designed for those who do not require medical detoxification or 24-hour supervision (McCarty et al., 2014). In TEDS, an intensive outpatient treatment program involves treatment of two or more hours at least three times per week. In contrast, non-intensive treatment consists of treatment fewer than three times per week and can be as limited as single-hour meetings every other week. As we describe in the introductory section, the literature highlights transportation issues as a significant barrier to treatment compliance.

Of relevance to our study, treatment settings impose different transportation demands, which suggests there will be heterogeneous effects of UberX entry across setting. Intensive outpatient is most demanding in terms of transportation, while non-intensive outpatient requires less frequent transportation, and detoxification and residential being the least demanding in terms of regular travel to the center for treatment. While UberX could impact admissions in all settings, we expect that effects will be largest for intensive outpatient, and finding the strongest effects for this modality would provide suggestive evidence that UberX reduces transportation barriers to facilitate healthcare use and not some other pathway.

Appendix Table A2 provides summary statistics from our main estimation sample derived from the TEDS data, weighted by CBSA population. There are 4.1 admissions of any type per 1,000 population per year, where non-intensive outpatient admissions are the most common subcategory at 1.79 per year (44% of the total), followed by detoxification at 1.02, residential at 0.76, and intensive outpatient at 0.53. We also report the proportion of CBSA-years in which UberX is present. We use UberX entry dates collected by Teltser et al. (2021), who expand on UberX entry dates provided by Hall et al. (2018). In Appendix B, we present

[11]For example, in 2018 — the final year of our study period — 0.2% of TEDS admissions were to hospital settings.

maps of CBSAs with available TEDS data that ever experienced UberX entry during the sample period, along with tables of initial entry dates by CBSA (regardless of TEDS data availability). Note that we do not control for the presence of Lyft, Uber's main competition. Lyft entry typically occurred after UberX entry and Lyft had a significantly smaller market share during our sample period.[12] We suspect that, all else equal, measurement error in treatment timing from omitting Lyft entry data will likely attenuate our estimates of interest.

3.2 Estimation

To estimate the effect of UberX entry on admissions to substance use disorder treatment, we use a difference-in-differences approach, exploiting variation in UberX entry across time and place. Our estimating equation is as follows:

$$y_{jt} = \alpha + \beta \cdot \text{Uber}_{jt} + X_{jt}\Pi + \theta_j + \phi_t + \varepsilon_{jt}. \tag{1}$$

In equation 1, y_{jt} refers to admissions to treatment in CBSA j in time period t (where y can be total, detoxification, residential, intensive outpatient, or non-intensive outpatient admissions). We capture UberX availability using an indicator, Uber_{jt}, that equals one if UberX enters CBSA j in year t and then remains equal to one for all subsequent time periods, and ignore any UberX exit and re-entry in any subsequent periods.[13] All specifications include CBSA fixed-effects, θ_j, time period (year) fixed-effects, ϕ_t, and an idiosyncratic error term, ε_{jt}. We cluster standard errors by CBSA. In some specifications, we include time-varying CBSA characteristics, such as the number of substance use disorder treatment centers, captured by the X_{jt} term. Our preferred specification weights observations by CBSA population.

[12] See https://www.vox.com/2018/12/12/18134882/lyft-uber-ride-car-market-share, website last accessed 4/23/2024.

[13] In our data, there are 24 UberX exits and half of those localities experience UberX re-entering the market within one year, suggesting that exits are not likely to lead to bias in our estimates.

If there are no unaccounted for idiosyncratic shocks that are correlated with both UberX entry and changes in substance use disorder treatment patterns, then β represents the causal impact of UberX entry on the outcome variable y_{jt}. If our identifying assumption is valid, the trend in outcome y in areas that UberX enters would be parallel to the trend in areas that UberX has not yet entered. That assumption is untestable, but we can examine trends prior to UberX entry using an event study approach. Following Jacobson et al. (1993), Goodman-Bacon and Cunningham (2019), and Teltser et al. (2021), our specification is outlined in equation 2:

$$y_{jt} = \sum_{k=-l}^{m} \beta_k \cdot 1(t - T_j = k) + X_{jt}\Pi + \theta_j + \phi_t + \varepsilon_{jt}. \tag{2}$$

The difference between equation 1 and equation 2 is that we replace the treatment variable for UberX's entrance in an area with a set of indicators $1(t - T_j = k)$, where T_j is the time that UberX launches in CBSA j, t is calendar time, and k is event time, or the number of periods relative to UberX launching in CBSA j. We consider l years prior to the CBSA's UberX entry date, and bin any observations in $t \leq -5$. Similarly, we consider m post UberX entry years, binned for any $t \geq 5$. We examine five years before and after UberX entry in an effort to balance the gains from examining a longer horizon with the costs associated with greater imbalance in the composition of CBSAs used to estimate each period coefficient.

Using equations 1 and 2 to estimate the effect of UberX on substance use disorder treatment patterns creates the potential for heterogeneous and dynamic treatment effect bias (Baker et al., 2022). This type of bias occurs in settings with staggered treatment adoption when the treatment effect is not constant over time. For example, UberX use tends to increase over time (Bagchi, 2018; Hall and Krueger, 2018). Equation 1 would therefore be misspecified because it imposes a constant, linear treatment effect. This type of misspecification can bias β in either direction. Using the Bacon decomposition procedure (Goodman-Bacon, 2021) to test for such issues (results not shown, but available on request), we find that 43% of our comparison groups involve contrasting later treated to earlier treated areas, known as "forbidden" comparisons because they can create a treatment effect bias (Borusyak et al., 2021). To avoid this bias we use the two stage difference-in-differences estimator proposed by Gardner (2022). This approach uses the untreated or not-yet-treated areas to estimate the relationships between time-varying covariates and fixed-effects.[14] The first stage uses those estimates to residualize the outcomes (i.e., treatment admissions) for both treated and untreated observations. In the second stage, the residualized outcomes are regressed on the treatment variable (using treated and untreated observations).[15]

4 Findings

We present our main findings in Table 1. In Panel A, we show the coefficient estimates from the simplest specification where the only covariates are CBSA and year fixed-effects. Here we find small positive effects on total, detoxification, and residential admissions, but none of these coefficient estimates are statistically significant at conventional levels. As described in Section 2, we expect to find smaller effects on admissions to detoxification or residential care. In contrast, we observe a decline in non-intensive outpatient admissions of 0.62 per 1,000 population per year (28%). The decline in non-intensive outpatient admissions is fully offset by an increase of 0.69 per 1,000 population per year in intensive outpatient admissions, which suggests that patients are able to receive more intensive treatment that also requires more transportation. Collectively, these estimates suggest that, while UberX has little to no effect on overall substance use disorder treatment admissions, the advent of ridesharing induces substitution from treatment options that are less transportation-intensive to those

[14] We focus on the not-yet-treated units (CBSAs) as our comparison group and we exclude 2019 TEDS data since we cannot estimate a year fixed-effect for 2019 when there are no remaining yet-to-be-treated CBSAs in 2019 in our sample.

[15] As an appendix item, we show the Borusyak et al. (2021) approach produces similar estimates.

that are more transportation-intensive. Further, to substitute from non-intensive to intensive outpatient treatment, many patients do not have to travel to a different provider. The majority of outpatient substance use disorder treatment centers (54%) provide both intensive and non-intensive treatment,[16] and TEDS data captures the movement from different treatment settings (such as a transition from non-intensive outpatient to intensive outpatient) as two separate treatment admissions (Substance Abuse and Mental Health Services Administration, 2022). With this in mind, the fact that we find offsetting effects on intensive and non-intensive outpatient admissions suggests that substitution occurs among new arrivals rather than mid-treatment switchers.

In Panel B of Table 1, where we include the per-capita number of treatment centers as an additional time-varying CBSA-level covariate, we find a very similar pattern of coefficient estimates. Specifically, we find a decrease of 0.54 non-intensive outpatient admissions with a corresponding increase of 0.68 intensive outpatient admissions. We have tested whether the absolute value of the non-intensive and intensive outpatient coefficient estimates are statistically different from each other using a non-parametric bootstrap (500 repetitions). The difference is not statistically significant at conventional levels (p-value = 0.577). Throughout the rest of our analyses, we use the Panel B specification as our preferred specification.

Because we use a staggered timing design, and as we explain in Section 3, we further support our identifying assumption using event studies that can tell us whether there are pre-trends that would undermine identification in our setting. In Figure 1, we present the Gardner (2022) two stage difference-in-differences event studies for all five admission measures, and find no evidence of differential pre-trends before UberX enters an area. Moreover, the event studies show that the effects grow over time. An increasing treatment effect over time aligns well with the observed patterns in the number of Uber driver-partners within cities,

[16] Authors' calculation based on the 2018 National Survey on Substance Abuse Treatment Services Survey (N-SSATS). N-SSATS, administered by SAMHSA, is used by the federal government to track the provision of substance use disorder treatment in the U.S.

as documented by Hall and Krueger (2018) using Uber's proprietary data. Their findings reveal a consistent monthly growth rate of over 4% after UberX entry, with an initial period of lower driver presence (typically six to 18 months) followed by a significant increase. Only Miami and Las Vegas exhibited significant deviations from this type of growth trajectory. The pattern also mirrors the trend in public interest towards Uber over time, as evidenced by Google Trends data (see Figure 1 of Hall et al., 2018).[17]

In Appendix Figure A2 we present the robustness of our intensive and non-intensive outpatient ("I-OP" and "NI-OP") admissions estimates. First, we vary the sample in the following ways: keep CBSAs with at least one treatment center, keep CBSAs with at least one center in all years 2008-2018, include all CBSAs observed in TEDS regardless of whether UberX entered, and exclude CBSAs that did not appear in TEDS in all years 2008-2018. Second, we use alternate specifications: unweighted regression, lag UberX entry by one year, and include an extended set of controls (e.g., state-by-year fixed-effects). Finally, we use the TEDS discharge (vs. admissions) data. Our observed pattern of substitution from non-intensive to intensive outpatient admissions is present in most alternative specifications, except when we include CBSAs that never experienced UberX entry. Notably, our main approach of omitting areas where UberX never enters aligns with the existing literature; such areas are unlikely to provide valid comparisons to areas where UberX entered.[18]

In Figure 2, we present heterogeneity estimates by race, age, and sex. We find that the magnitude of substitution is largest among individuals aged 18 to 34 years, the core group of

[17]Note that we observe a small increase in residential care five years after UberX entry, which reflects the difference in residential care between the areas treated in 2012 and 2013 relative to areas that were not-yet-treated in 2017 and 2018. This finding hints at a couple of speculative possibilities that we unfortunately cannot meaningfully probe. First, this finding may simply be attributable to the changing sample composition in the later post-treatment yearly estimates. Second, patients may become more engaged in treatment after receiving more intensive outpatient care, and perhaps those with more severe substance use disorders eventually take up higher levels of care.

[18]Excluding areas where UberX never enters for our main analyses follows some earlier literature, such as Teltser et al. (2021). Moreover, the literature has demonstrated that (a) population is the strongest predictor of UberX entry and (b) UberX entered most metropolitan and micropolitan areas by 2018 (e.g., Hall et al., 2018; Zhou, 2020), implying that areas lacking UberX by 2018 were relatively rural and very low population.

UberX and smartphone users during the sample period (Smith, 2016). We see this finding as strong evidence in favor of a causal interpretation for our findings. We also observe larger effects among men and minority groups. We suspect the pattern is related to the fact that many referrals to substance use outpatient treatment come from the criminal justice system (including individuals who are on probation, parolees, etc.).

In Figure 3, we present area-level heterogeneity estimates, and find the magnitude of substitution is largest among CBSAs that are in Affordable Care Act non-Medicaid-expansion states, those with below median per-capita number of treatment centers, those with below-median population, and those with below-median Transit Connectivity Index ("TCI") scores.[19] These TCI scores come from the Center for Neighborhood Technology (CNT) (The Center for Neighborhood Technology, 2024). The CNT's goal is to provide a "robust, one of a kind database consisting of stop, route and frequency information for 902 transit agencies in regions with populations greater than 100,000 as well as a large number of smaller regions and agencies." The TCI scores offer a summary of the overall transit quality and connectivity of each area.[20] These area-level heterogeneity estimates offer further support for a causal interpretation of our findings as effect sizes are largest among those groups and geographic areas that one would ex-ante predict the greatest impact (lower population, non-Medicaid expansion, fewer centers per capita, etc.), suggesting that ridesharing has a relatively large impact on people and areas where access to appropriate care was more challenging prior to the advent of ridesharing in the area.

In Figure 4, we examine heterogeneity by source of referral (criminal justice vs. non-criminal justice), prior treatment history (no treatment vs. previous treatment), and co-

[19]We also examine whether effects vary by states' paid sick leave mandates, which can allow patients to take financially protected time away from work for their own treatment or to support dependents' treatment (National Partnership for Women & Families, 2023). However, we do not find any clear heterogeneity across states with and without paid sick leave mandates.

[20]We use the CBSA-level TCI from the Center for Neighborhood Technology's AllTransit website (The Center for Neighborhood Technology, 2024).

occurring mental health disorder at admission. We find evidence to suggest that our estimates are primarily related to criminal justice system referrals, which includes courts, probation officers, and parole supervisors.[21] The estimates suggest that probation and parole officers are aware of how ridesharing can help those who need treatment to access care. Across prior treatment status, we see similar evidence of substitution between intensive and non-intensive treatment. When we examine those with and without a co-occurring mental health disorder, we see a similar pattern but the estimated effects are smaller in magnitude. The smaller effect size is appropriate given this is a subset of all admissions.

In Appendix Table A3, we report estimates using procedures robust to heterogeneous treatment effects proposed by Borusyak et al., 2021). The pattern of coefficient estimates is very similar to our main findings using the methods developed by Gardner (2022).

Finally, we estimate a "leave-one-out" analysis in which we sequentially remove each CBSA that has an UberX entry by 2018 (262 CBSAs) from our sample and estimate the effect of UberX entry in the other 261 CBSAs. Those coefficient estimates are reported, sorted by treatment effect size, in Appendix Figure A3 and are very similar across the leave-one-out samples. While not shown in the figure, each coefficient estimate in the "leave-one-out" analyses are significant at the 5% level or greater.

4.1 UberX's Effect on Substance Use as a Threat to Identification

Overall, our analysis shows an increase in the proportion of patients receiving intensive outpatient care after the advent of UberX in an area. However, one significant potential threat to identification is that UberX may increase substance use (Zhou, 2020; Teltser et al., 2021). We contend that such substance use is not driving the patterns in treatment that we observe in the TEDS data. First, research shows that the typical person with substance

[21] Probation being one alternative to incarceration for low-level offenses and parole referring to a period of supervision after release from incarceration.

use order does not receive treatment for several years following disease onset (Kessler et al., 2001), while we observe changes in treatment modality starting one to two years post-UberX entry. A second reason is that we would expect to see an increase in total, detoxification, residential, and non-intensive outpatient admissions if there were increased substance use that required treatment. Instead, we see an increase in admissions primarily for the type of treatment where patients might experience ongoing transportation challenges, and a *decrease* in non-intensive outpatient, which is the most common modality among all patients (see Appendix Figure A1) as well as among patients with no prior treatment history.[22] We also do not observe an overall increase in admissions relating to criminal justice referrals, like we would expect to see if increased substance use were driving our findings. Rather, changes in the number of referrals to intensive versus non-intensive outpatient treatment from the criminal justice system drive our main findings. This pattern could either be explained by changes in decision-making among officers of the court, or by defendants and their lawyers being more willing to suggest intensive outpatient treatment in sentence bargaining.

Finally, in Appendix Table A4, we find that the proportion of intensive and non-intensive outpatient admissions who report daily substance use is either flat or declining. We also find that treatment duration and the proportion of successfully completed treatment episodes increase after the introduction of UberX. These estimates provide further evidence that the change in treatment patterns is driven by transportation availability; we would not suspect an increase in substance use due to UberX to also cause an increase in treatment adherence.

5 Conclusion

We study whether ridesharing affects healthcare utilization by examining substance use disorder treatment admissions in the U.S. Overall, we find that ridesharing primarily affects

[22]In the 2008-2018 TEDS, 39.7% of all patients have no prior treatment history and this share is 46.1% among patents in non-intensive outpatient.

modality of treatment rather than the number of individuals receiving treatment, evidenced by increases in intensive outpatient care (which is more transportation-intensive due to the greater frequency of care) and offsetting decreases in non-intensive outpatient care.

An increase in intensive outpatient treatment, coupled with a decline in non-intensive outpatient treatment, suggests there is significantly more healthcare being provided, even without an increase in total admissions. Intensive care is likely more appropriate for more severe substance use disorder cases. Therefore, to the extent that people feel like they cannot obtain enough treatment, including due to transportation-related barriers, our findings suggest that ridesharing can improve access to care.

Our findings are strongest for young adults (18-34 years old). In addition to being the age group most likely to use UberX during our study period (Smith, 2016), many substance use disorders emerge during young adulthood (Kessler et al., 2005). Treatment received during this stage likely shapes substance use disorders across one's lifetime. Indeed, previous economic research demonstrates that policy shocks during this stage can substantially alter substance use through middle-age (Kaestner and Yarnoff, 2011; Maclean, 2015).

Understanding how ridesharing affects substance use disorder treatment access helps us better understand the broader consequences associated with the introduction of ridesharing. Our work contributes by showing that UberX has caused significant changes in the intensity of healthcare utilization among individuals engaging in treatment for substance use disorders.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

During the preparation of this work the authors used Google's Gemini AI to rephrase portions of descriptive text. After using this tool, the authors reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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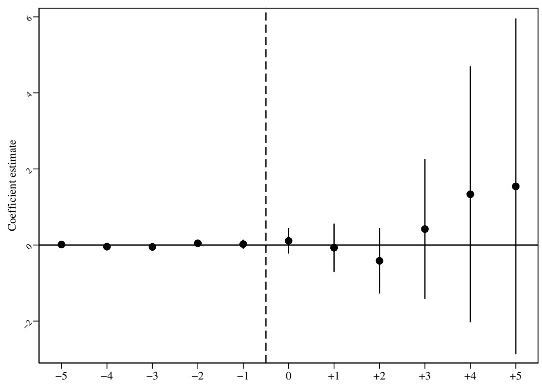
Tables and Figures

Table 1: Effect of UberX Entry on Admissions per 1,000 (by Setting) to Substance Use Disorder Treatment using Gardner 2SDiD: TEDS 2008-2018

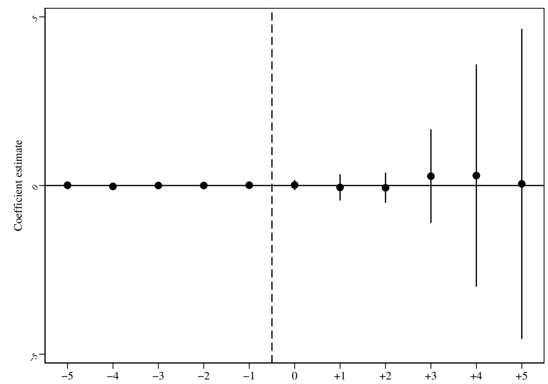
	Total	Detoxification	Residential	Intensive Outpatient	Non-intensive Outpatient
	(1)	(2)	(3)	(4)	(5)
Panel A: CBSA and Year Fixed-effects Only					
UberX	0.33	0.11	0.14	0.69***	-0.62**
	(0.75)	(0.73)	(0.11)	(0.22)	(0.27)
Panel B: Controlling for Fixed-effects and Number of Treatment Centers Per Capita (Main Sample & Specification)					
UberX	0.38	0.08	0.15	0.68***	-0.54**
	(0.78)	(0.71)	(0.11)	(0.21)	(0.23)
Pre-treatment mean	4.85	1.13	0.89	0.63	2.21
Observations	2,801	2,801	2,801	2,801	2,801

Notes: 2SDiD = two-stage difference-in-differences (Gardner, 2022). All estimates include only areas where UberX ever enters. In Panel A, the regression specification includes CBSA fixed-effects and year fixed-effects. We then control for the number of treatment centers per capita in Panel B, and use this as our base specification for our event studies and heterogeneity analyses. The unit of observation is a CBSA in a year. Data are TEDS 2008 to 2018. Our regressions weight observations by CBSA population. Standard errors are clustered at the CBSA level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

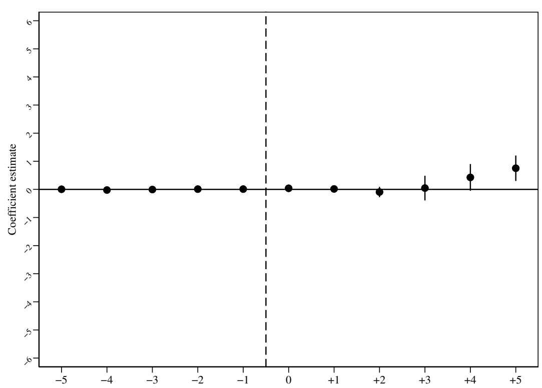
Figure 1: Event Studies



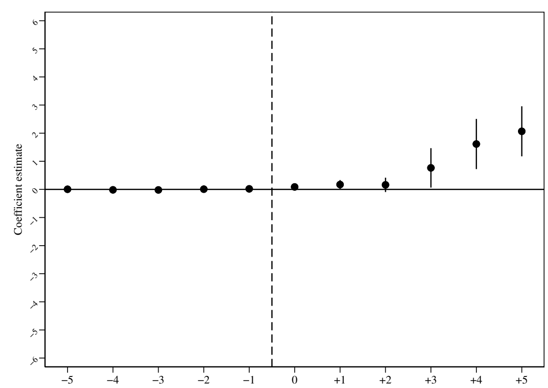
(a) Total Admissions



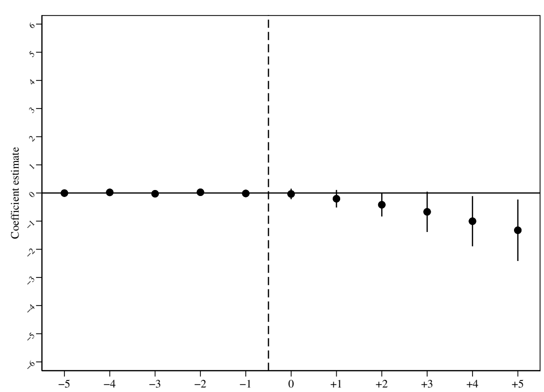
(b) Detoxification



(c) Residential



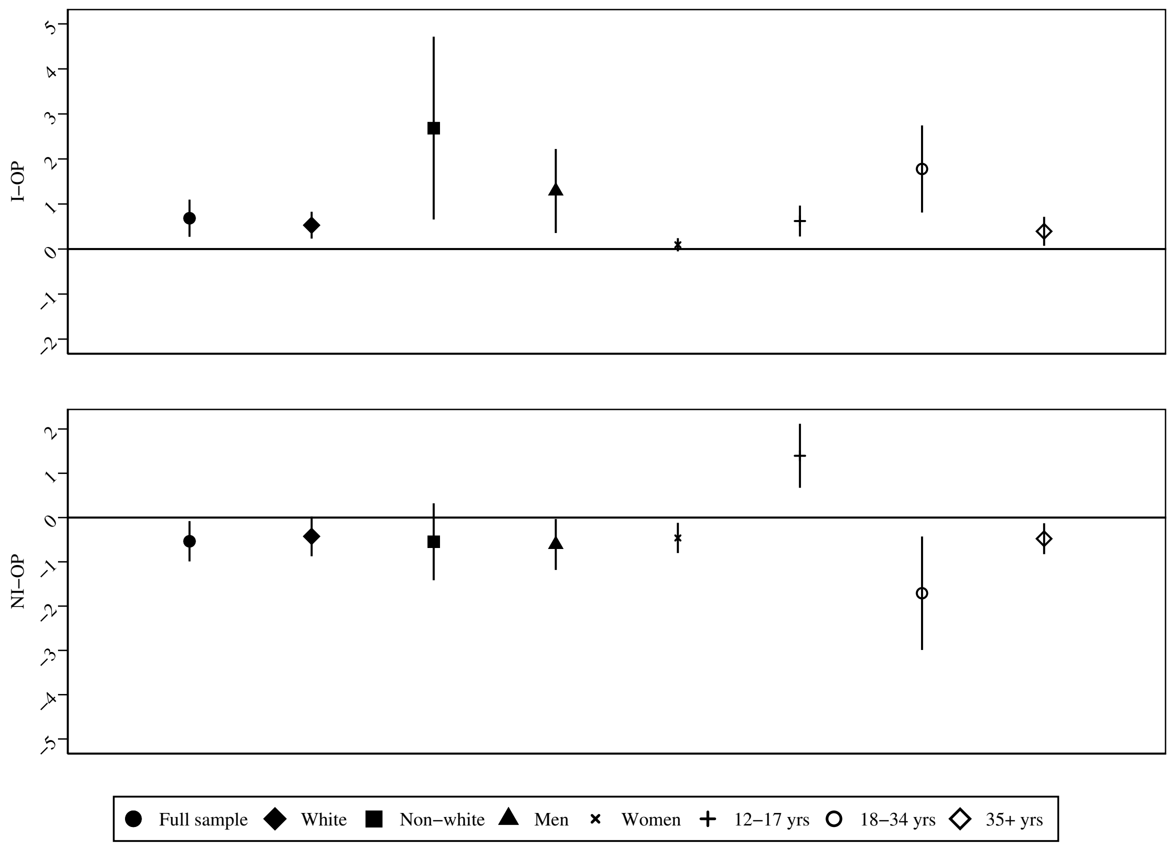
(d) Intensive Outpatient



(e) Non-intensive Outpatient

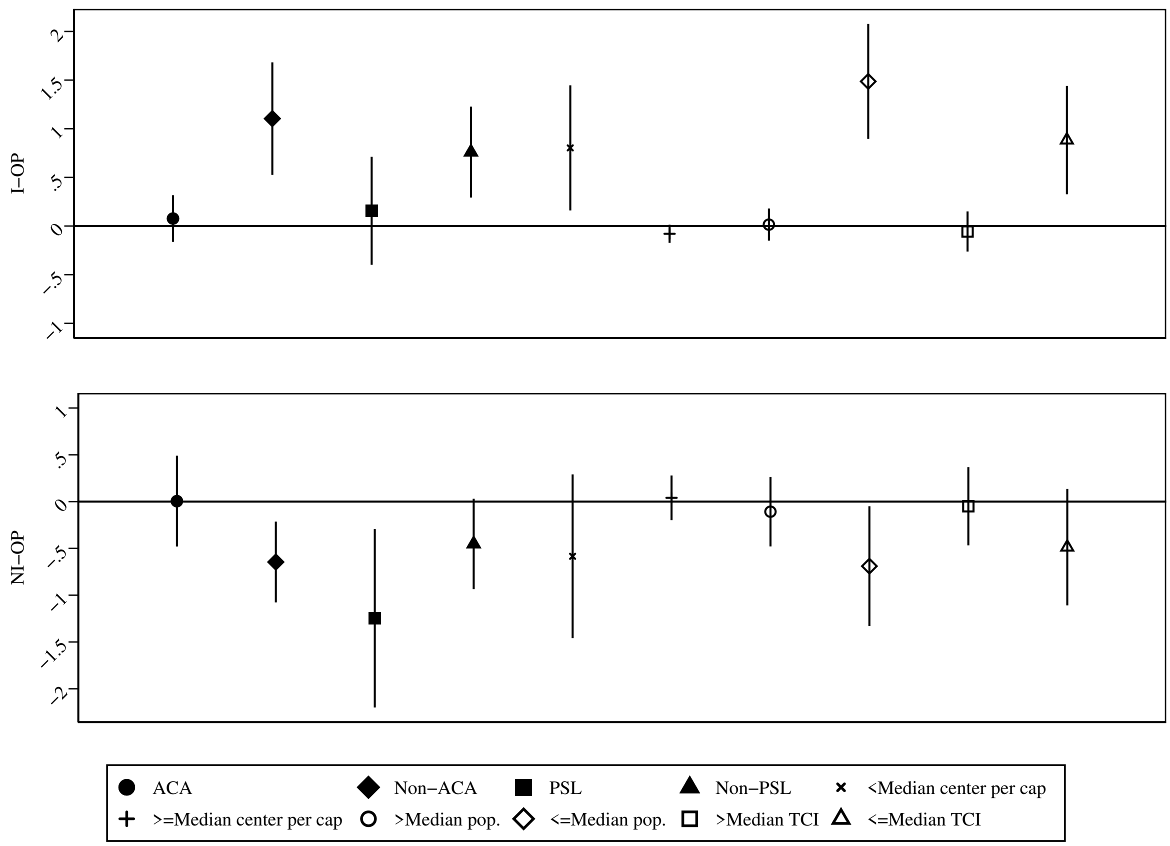
Notes: These event-study figures show the effect of UberX entry on the noted outcome per 1,000 population using the two-step procedure from Gardner (2022) and TEDS data from 2008-2018. Coefficient estimates are reported with circles. 95% confidence intervals that account for within-CBSA clustering are reported with vertical lines. We control for the number of substance use disorder treatment centers per 1,000 residents, CBSA fixed-effects, and year fixed-effects in each specification. The unit of observation is a CBSA in a year. Data are weighted by the CBSA population.

Figure 2: Demographic Heterogeneity of Intensive vs. Non-Intensive Outpatient Effects



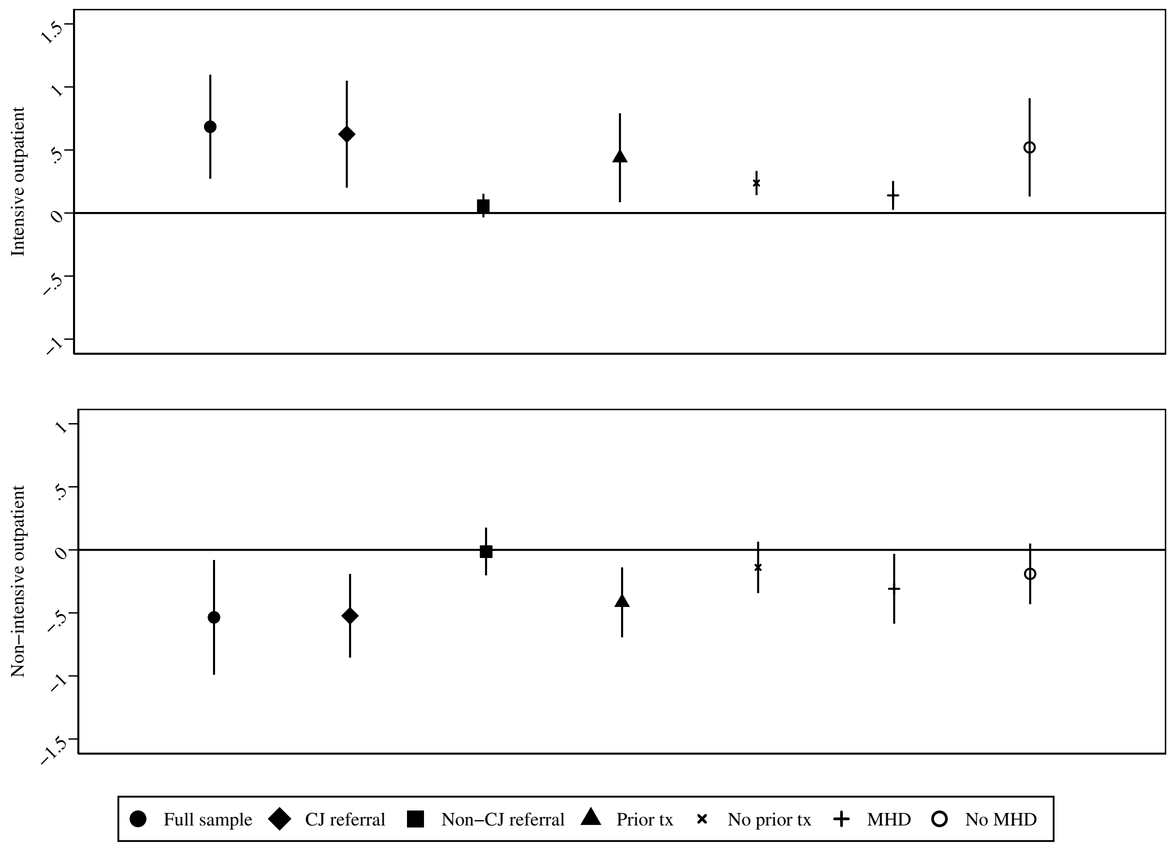
Notes: We report the effect of UberX entry on the intensive vs. non-intensive outpatient changes per 1,000 population for various demographic subgroups. Estimation uses the Gardner (2022) two-step procedure and TEDS data from 2008-2018. The legend explains the relevant subgroup sample restriction that we use to produce the coefficient estimate. These include race, sex, and age subgroups. 95% confidence intervals that account for within-CBSA clustering are reported with vertical lines. We control for the number of substance use disorder treatment centers per 1,000 residents, CBSA fixed-effects, and year fixed-effects in each specification. The unit of observation is a CBSA in a year. Data are weighted by the CBSA population.

Figure 3: Area-Level Heterogeneity of Intensive vs. Non-Intensive Outpatient Effects



Notes: We report the effect of UberX entry on the Intensive vs. Non-Intensive Outpatient changes per 1,000 population by area characteristics. Estimation uses the Gardner (2022) two-step procedure and TEDS data from 2008-2018. The legend explains the relevant sample restriction that produces the coefficient estimate. These include ACA vs. Non-ACA, referring to Affordable Care Act Medicaid expansion, and PSL vs. non-PSL, referring to the presence of paid sick leave mandates at the state level. The remaining estimates estimate the treatment effect of UberX in CBSAs with above vs. below median treatment centers per capita, population, and transportation connectivity ("TCI" score; The Center for Neighborhood Technology, 2024). 95% confidence intervals that account for within-CBSA clustering are reported with vertical lines. We control for the number of SUD treatment centers per 1,000 residents, CBSA fixed-effects, and year fixed-effects in each specification. The unit of observation is a CBSA in a year. Data are weighted by the CBSA population.

Figure 4: Clinical Characteristic Heterogeneity of Intensive vs. Non-Intensive Outpatient Effects



Notes: We report the effect of UberX entry on the intensive vs. non-intensive outpatient admissions per 1,000 population by clinical characteristics. Estimation uses the Gardner (2022) two-step procedure and TEDS data from 2008-2018. The legend explains the relevant sample restriction that produces the coefficient estimate. These include subsample analyses focusing on criminal justice (CJ) versus non-CJ referrals, prior treatment (tx) versus not having had prior treatment, and being admitted with a co-occurring mental health disease (MHD). 95% confidence intervals that account for within-CBSA clustering are reported with vertical lines. We control for the number of substance use disorder treatment centers per 1,000 residents, CBSA fixed-effects, and year fixed-effects in each specification. The unit of observation is a CBSA in a year. Data are weighted by the CBSA population.

Appendix A Additional Figures and Tables

In Figure A1 we show the trends in admissions per 1,000 residents to different types of SUD treatment over time. In Table A2 we provide summary statistics for our main outcomes and key independent variables.

In Figure A2 we present the robustness of our intensive and non-intensive outpatient ("I-OP" and "NI-OP") admissions estimates to alternative sample and specification choices, including restricting to CBSAs with at least one treatment center, keeping all CBSAs regardless of whether UberX ever entered, unweighted regressions, lagging the treatment variable one year, including state-by-year fixed-effects, and more.

In Figure A3, we present an ordered histogram of coefficient estimates for intensive and then non-intensive substance use disorder treatment where we sequentially remove the data for one CBSA from our sample, repeat our estimates, store the coefficients, and then restore that CBSA to the sample before removing data related to the next CBSA. We then plot all of the coefficients from that exercise, sorted by treatment effect size. Note that plotting the associated standard errors is not feasible given the number of CBSAs in our sample relative to the space available. However, we note here that all coefficient estimates are statistically significant at the 5% level or greater.

In Table A1, we present demographic characteristics of patients in substance use disorder treatment for TEDS 2008-2018. As we mention in the text, patients admitted to TEDS-tracked centers are younger and observably less advantaged than the general U.S. population. For instance, 50% of admissions are between ages 18 and 34 years, with 44% aged 35 to 64 years. Men are substantially more likely to appear in the TEDS data than women: 66% vs. 34%. While the plurality of patients admitted to TEDS-tracked centers are White (71%), the patient population is more racially and ethnically diverse than the overall U.S. population with 16% of patients reporting Black race and 13% reporting another race. Additionally, 13%

report Hispanic ethnicity.[A1] Just 5.2% of patients report a college degree and only 17% work full-time. The most commonly listed substances are alcohol (38%) and opioids (27%).[A2] Our data also shows that 35% of patients have a diagnosed mental health disorder.

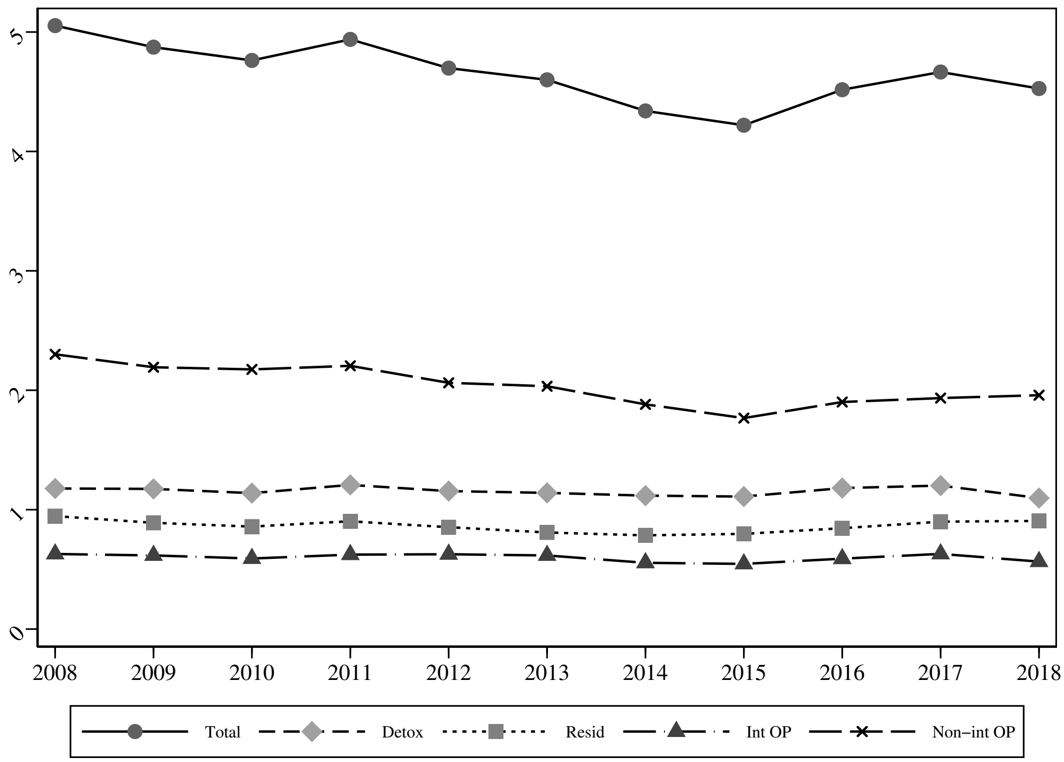
In Table A2, we present summary statistics for our main outcome variables. Area level population data are drawn from the National Cancer Institute (NCI) SEER, and treatment center counts come from the U.S. Census County Business Patterns dataset (U.S. Census Bureau, 2022). We use NAICS codes 623220 (residential mental health and substance abuse centers) and 621420 (outpatient mental health and substance abuse centers) following the literature (Swensen, 2015; Deza et al., 2022). We cannot isolate mental health treatment from substance use disorder treatment in the data. In Table A3 we present Borusyak et al. difference-in-difference imputation estimates as an additional robustness check.

Finally, in Table A4, we present estimates for changes in the proportion of admissions to intensive and non-intensive outpatient treatment with daily substance use. We present similar estimates for duration of stay (in days) and the proportion successfully completing treatment. These estimates highlight that there is no significant increase in the proportion of patients admitted to outpatient treatment who are using substances daily. Moreover, these estimate show that the advent of ridesharing in a CBSA is associated with longer stays and an increase in successful completion of treatment. We would not expect these patterns if the advent of ridesharing was driving our findings primarily by causing increased substance use.

[A1] Race and ethnicity information are based on two separate variables.

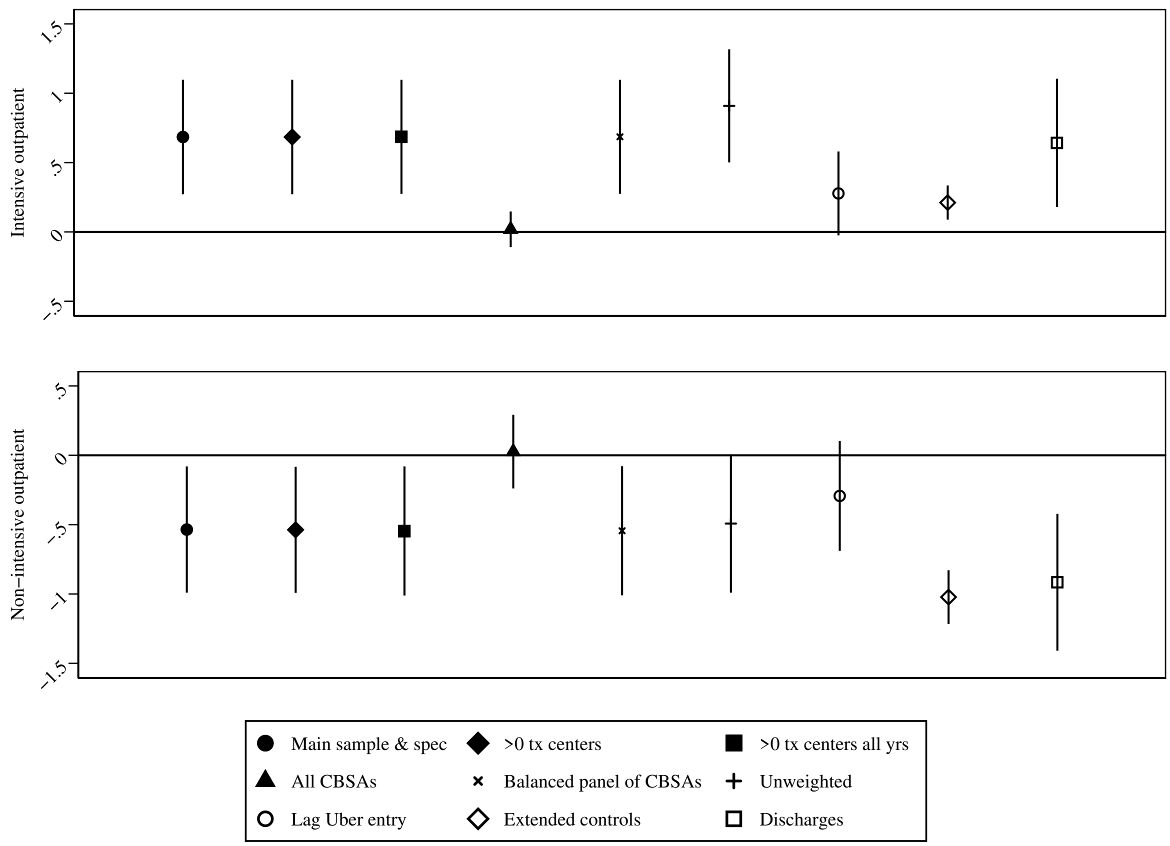
[A2] We report the primary substance listed at admission. TEDS records up to three substances.

Figure A1: Trends in Admissions per 1,000 Population to Substance Use Disorder Treatment



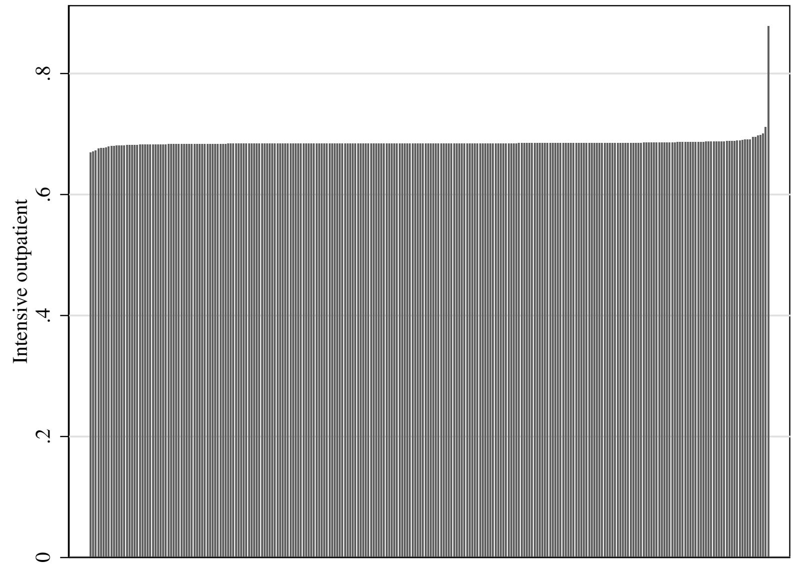
Notes: TEDS 2008-2018. The unit of observation is a year. Data are weighted by CBSA population.

Figure A2: Robustness of Intensive vs. Non-Intensive Outpatient Effects

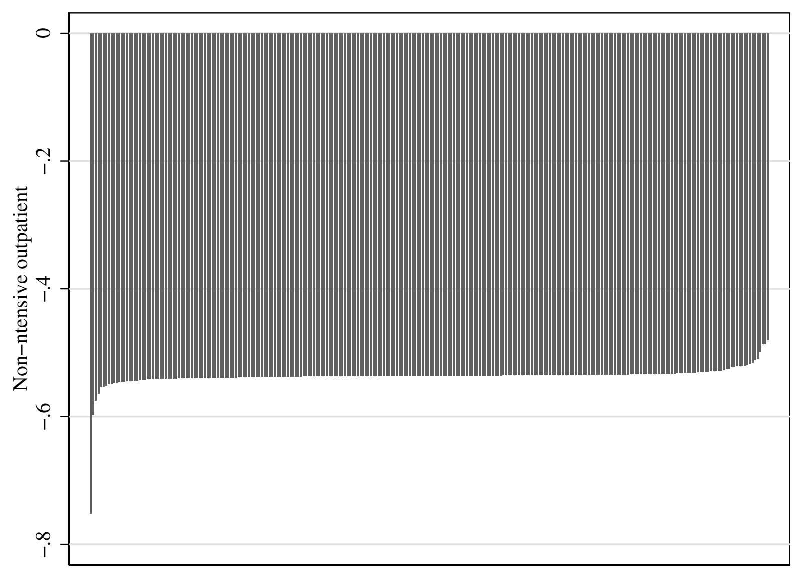


Notes: We report the effect of UberX entry on intensive vs. non-intensive outpatient changes per 1,000 population as a function of various sample and data restrictions and choices. Estimation uses the Gardner (2022) two-step procedure and TEDS data from 2008-2018. The legend summarizes the relevant sample restriction or data choice used to produce the coefficient estimate. These include restricting the sample to only those areas where we have data for at least one treatment center data (>0 tx centers, and then the more restrictive >0 tx centers all years), expanding the sample to include all CBSAs, a balanced panel, showing estimates without weighting, lagging Uber entry by one year, including an extended set of controls that includes state-by-year fixed-effects and transit connectivity ("TCI score"), and examining the change in discharges. 95% confidence intervals that account for within-CBSA clustering are reported with vertical lines. We control for the number of substance use disorder treatment centers per 1,000 residents, CBSA fixed-effects, and year fixed-effects in each specification. The unit of observation is a CBSA in a year. Data are weighted by the CBSA population.

Figure A3: Leave-one-out Analyses



(a) Intensive Treatment



(b) Non-intensive Treatment

Notes: Figures show an ordered histogram of coefficient estimates for intensive non-intensive substance use disorder treatment where we remove one CBSA from our sample at a time. Estimation uses the Gardner (2022) two-step procedure and TEDS data from 2008-2018. Plotting the standard errors of each estimate is not possible given the number of CBSAs in our sample. However, we note that all coefficient estimates are statistically significant at the 5% level or greater. In the intensive outpatient analysis, excluding the Shreveport-Bossier City, LA CBSA yields the largest coefficient estimate, while dropping the Bridgeport-Stamford-Norwalk, CT CBSA yields the smallest coefficient estimate. In the non-intensive outpatient analysis, excluding the Shreveport-Bossier City, LA CBSA yields the largest (in absolute value) coefficient estimate while dropping the Rochester, NY CBSA yields the smallest (in absolute value) coefficient estimate.

Table A1: Demographics of Patients in Substance Use Disorder Treatment: TEDS 2008-2018

Variable:	Proportion
12-17 yrs	0.057
18-34 yrs	0.50
35-64 yrs	0.44
65+ yrs	0.0078
Male	0.66
Female	0.34
White	0.71
Black	0.16
Other race	0.13
Hispanic	0.13
Non-Hispanic	0.87
Less than high school	0.31
High school	0.45
Some college	0.19
College degree	0.052
Full-time work	0.17
Part-time work	0.081
Unemployed	0.41
Not in labor force	0.34
Alcohol	0.38
Cocaine	0.067
Marijuana	0.17
Opioid	0.27
Stimulant	0.10
Benzodiazepines	0.0098
Other substance	0.017
Mental health disorder	0.35
Observations	7,459,577

Note: The unit of observation is patient a CBSA in a year.

Table A2: Summary Statistics for TEDS 2008 - 2018 and UberX Entry Data

Variable:	Mean
Total admissions per 1,000	4.65
Detoxification admissions per 1,000	1.15
Residential admissions per 1,000	0.86
Intensive outpatient admissions per 1,000	0.60
Non-intensive outpatient admissions per 1,000	2.03
UberX present (unweighted)	0.37
Treatment centers (unweighted)	49.6
Population (unweighted)	899,924
CBSA-Year Observations	2,801

Note: The unit of observation is a CBSA in a year. Admissions counts per capita are weighted by CBSA population. Data: TEDS, County Business Patterns, and NCI SEER population data from ever-treated CBSAs from 2008-2018.

Table A3: Effect of UberX Entry on Admissions per 1,000 (by Setting) to Substance Use Disorder Treatment using Borusyak et al. (2021): TEDS 2008-2018

	Total	Detoxification	Residential	Intensive Outpatient	Non-intensive Outpatient
	(1)	(2)	(3)	(4)	(5)
UberX	0.38	0.08	0.15	0.69***	-0.53***
	(0.79)	(0.73)	(0.11)	(0.21)	(0.23)
Pre-treatment mean	4.85	1.13	0.89	0.63	2.21
Observations	2,799	2,799	2,799	2,799	2,799

Notes: All estimates include only areas where UberX ever enters and control for the number of substance use disorder treatment centers per capita. Estimation uses the Gardner (2022) two-step procedure and TEDS data from 2008-2018. The unit of observation is a CBSA in a year. Data are TEDS 2008 to 2018. Our regressions weight observations by CBSA population. Standard errors are clustered at the CBSA level and are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A4: Effect of UberX Entry on Daily-Use Admissions and Treatment Outcomes

	Daily Use		Length of Stay		Successfully Completed	
	Intensive Outpatient	Non-intensive Outpatient	Intensive Outpatient	Non-intensive Outpatient	Intensive Outpatient	Non-intensive Outpatient
UberX Entry	-0.03**	0.00	10.38	19.58**	0.09**	0.04*
	(0.02)	(0.01)	(7.88)	(9)	(0.04)	(0.02)
Pre-treatment mean	0.27	0.24	104.53	134.83	0.32	0.38
Observations	2,379	2,738	2,060	2,235	2,060	2,235

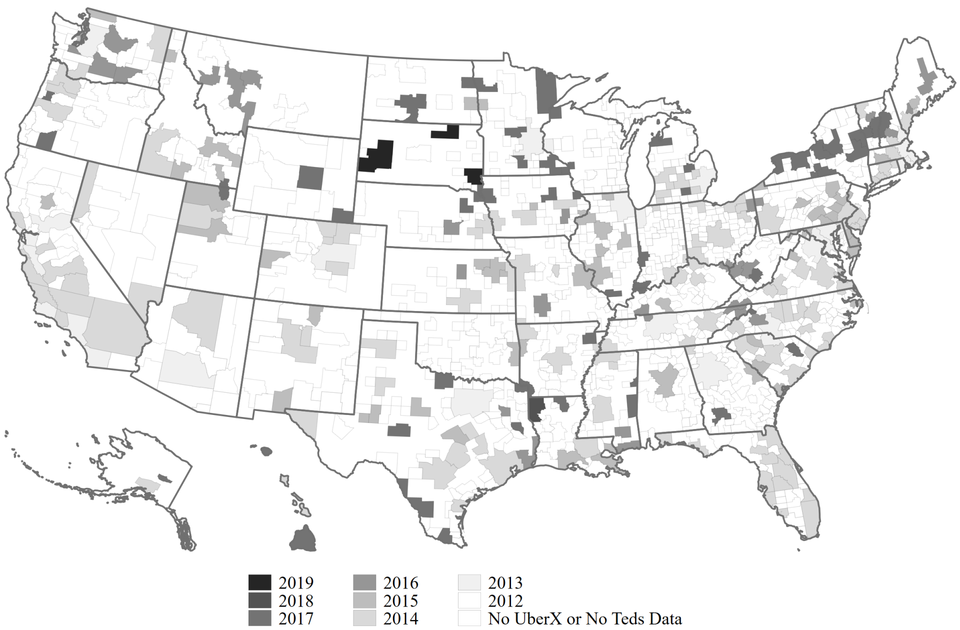
Notes: All estimates include only areas where UberX ever enters and control for the number of substance use disorder treatment centers per capita. Estimation uses the Gardner (2022) two-step procedure and TEDS data from 2008-2018. The unit of observation is a CBSA in a year. Data are TEDS 2008 to 2018. Our regressions weight observations by CBSA population. Standard errors are clustered at the CBSA level and are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix B Uber Entry Dates and Maps

In this section we provide a complete list of all UberX entry dates, regardless of whether we have TEDS data for that area. We are confident in our work, but, as with any hand collected data, we cannot be certain they are 100% accurate.

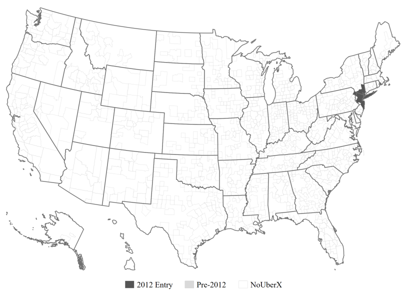
We also offer a series of maps showing UberX entry through 2019 along with maps showing UberX entry dates across CBSAs by year. These maps only indicate Uber entry if we also have TEDS data for the area. Unshaded areas in the map are the union of CBSAs with no indicated UberX entry during the sample period and CBSAs with no TEDS data.

Figure B1: Entry of UberX by CBSA

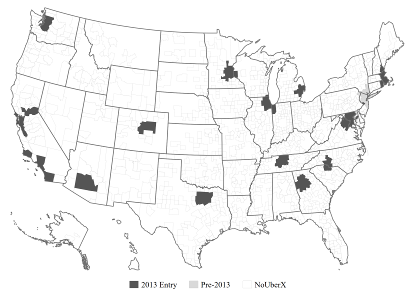


Note: This map shows all CBSAs in grey outline. Areas with no known UberX entry date or without TEDS data are white. Areas that ever experience UberX entry by the end of 2019 are shaded grey according to their year of entry. Darker colors indicate earlier UberX entry. Note that CBSAs with 2019 UberX entry serve only as control areas in our analyses.

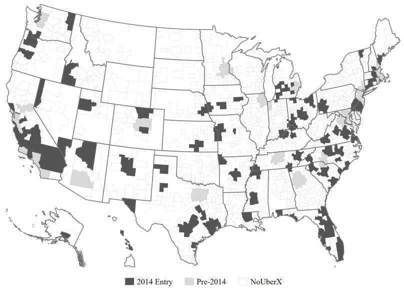
Figure B2: Entry of UberX By CBSA Over Time



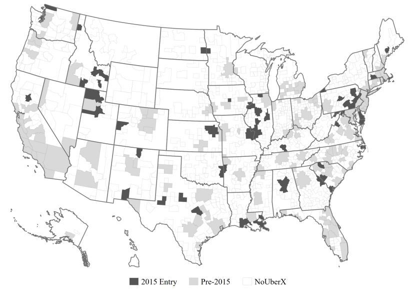
(a) 2012 UberX Entry



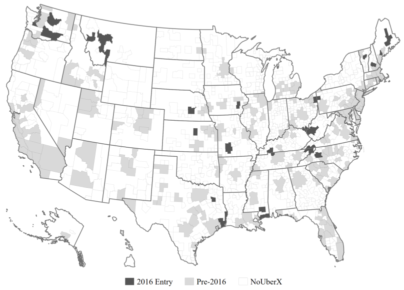
(b) 2013 UberX Entry



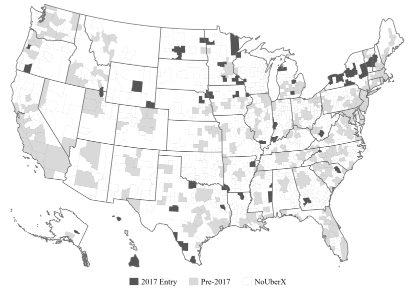
(c) 2014 UberX Entry



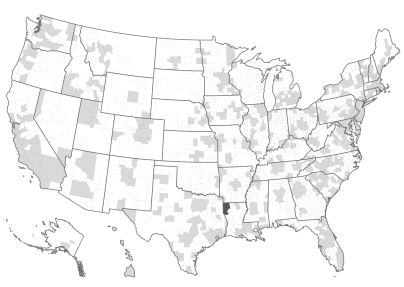
(d) 2015 UberX Entry



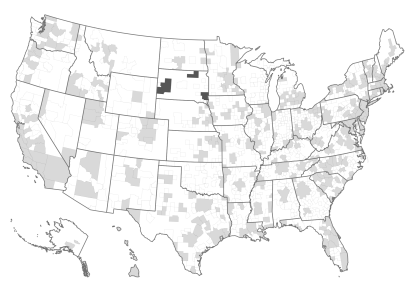
(e) 2016 UberX Entry



(f) 2017 UberX Entry



(g) 2018 UberX Entry



(h) 2019 UberX Entry

Note: Map shows all CBSAs (grey outline). Areas with no known UberX entry date as of that year or without TEDS data are white. Areas that experience UberX entry in the noted year are shaded black and areas that have previously experience entry are shaded grey. Note that CBSAs with 2019 UberX entry serve only as control areas in our analyses.

Table B1: Complete Uber Entry Dates 1 of 7

CBSA Area/Division Code	CBSA Area/Division Title	Date UberX Entered	CBSA Area/Division Code	CBSA Area/Division Title	Date UberX Entered
(1)	(2)	(3)	(1)	(2)	(3)
20524*	Dutchess County-Putnam County, NY	08/24/2012	40900	Sacramento–Roseville–Arden-Arcade, CA	09/30/2013
35614*	New York-Jersey City-White Plains, NY-NJ	08/24/2012	19740	Denver-Aurora-Lakewood, CO	10/04/2013
36084*	Oakland-Hayward-Berkeley, CA	01/18/2013	46060	Tucson, AZ	10/10/2013
41884*	San Francisco-Redwood City-South San Francisco, CA	01/18/2013	36420	Oklahoma City, OK	10/30/2013
42034*	San Rafael, CA	01/18/2013	42200	Santa Maria-Santa Barbara, CA	10/31/2013
11244*	Anaheim-Santa Ana-Irvine, CA	03/14/2013	19804*	Detroit-Dearborn-Livonia, MI	10/31/2013
31084*	Los Angeles-Long Beach-Glendale, CA	03/14/2013	47664*	Warren-Troy-Farmington Hills, MI	10/31/2013
42644*	Seattle-Bellevue-Everett, WA	04/11/2013	19124*	Dallas-Plano-Irving, TX	11/05/2013
16974*	Chicago-Naperville-Arlington Heights, IL	04/22/2013	12580	Baltimore-Columbia-Towson, MD	11/06/2013
20994*	Elgin, IL	04/22/2013	45940	Trenton, NJ	11/13/2013
29404*	Lake County-Kenosha County, IL-WI	04/22/2013	35084*	Newark, NJ-PA	11/13/2013
41740	San Diego-Carlsbad, CA	05/09/2013	34980	Nashville-Davidson–Murfreesboro–Franklin, TN	12/10/2013
14454*	Boston, MA	06/04/2013	41500	Salinas, CA	02/04/2014
15764*	Cambridge-Newton-Framingham, MA	06/04/2013	42100	Santa Cruz-Watsonville, CA	02/04/2014
40484*	Rockingham County-Strafford County, NH	06/04/2013	23420	Fresno, CA	02/05/2014
12060	Atlanta-Sandy Springs-Roswell, GA	06/26/2013	26420	Houston-The Woodlands-Sugar Land, TX	02/21/2014
35004*	Nassau County-Suffolk County, NY	07/01/2013	18140	Columbus, OH	02/25/2014
41940	San Jose-Sunnyvale-Santa Clara, CA	07/24/2013	31540	Madison, WI	03/06/2014
43524*	Silver Spring-Frederick-Rockville, MD	08/08/2013	38300	Pittsburgh, PA	03/13/2014
47894*	Washington-Arlington-Alexandria, DC-VA-MD-WV	08/08/2013	17140	Cincinnati, OH-KY-IN	03/27/2014
33460	Minneapolis-St. Paul-Bloomington, MN-WI	09/04/2013	46140	Tulsa, OK	03/27/2014
26900	Indianapolis-Carmel-Anderson, IN	09/05/2013	33340	Milwaukee-Waukesha-West Allis, WI	03/28/2014
38060	Phoenix-Mesa-Scottsdale, AZ	09/05/2013	41700	San Antonio-New Braunfels, TX	03/28/2014
39300	Providence-Warwick, RI-MA	09/12/2013	14860	Bridgeport-Stamford-Norwalk, CT	04/01/2014
16740	Charlotte-Concord-Gastonia, NC-SC	09/27/2013	47220	Vineland-Bridgeton, NJ	04/01/2014

Notes: Wherever UberX entry is specified at the Core Based Statistical Area (CBSA) Division level, these cases are denoted by a star in column (1). Otherwise CBSA codes and titles refer to Core Based Statistical Areas.

Table B2: Complete Uber Entry Dates 2 of 7

CBSA Area/Division Code (1)	CBSA Area/Division Title (2)	Date UberX Entered (3)	CBSA Area/Division Code (1)	CBSA Area/Division Title (2)	Date UberX Entered (3)
15804*	Camden, NJ	04/01/2014	33124*	Miami-Miami Beach-Kendall, FL	06/04/2014
33874*	Montgomery County-Bucks County-Chester County, PA	04/01/2014	46520	Urban Honolulu, HI	06/12/2014
33700	Modesto, CA	04/02/2014	12540	Bakersfield, CA	06/13/2014
40140	Riverside-San Bernardino-Ontario, CA	04/03/2014	30460	Lexington-Fayette, KY	06/13/2014
17460	Cleveland-Elyria, OH	04/08/2014	45780	Toledo, OH	06/13/2014
45104*	Tacoma-Lakewood, WA	04/08/2014	20500	Durham-Chapel Hill, NC	06/26/2014
45300	Tampa-St. Petersburg-Clearwater, FL	04/11/2014	21340	El Paso, TX	06/26/2014
11460	Ann Arbor, MI	04/22/2014	22180	Fayetteville, NC	06/26/2014
31140	Louisville/Jefferson County, KY-IN	04/24/2014	24660	Greensboro-High Point, NC	06/26/2014
32820	Memphis, TN-MS-AR	04/24/2014	31180	Lubbock, TX	06/26/2014
35300	New Haven-Milford, CT	04/24/2014	48900	Wilmington, NC	06/26/2014
39580	Raleigh, NC	04/26/2014	49180	Winston-Salem, NC	06/26/2014
10740	Albuquerque, NM	04/30/2014	12100	Atlantic City-Hammonton, NJ	06/27/2014
47260	Virginia Beach-Norfolk-Newport News, VA-NC	05/01/2014	36140	Ocean City, NJ	06/27/2014
17820	Colorado Springs, CO	05/02/2014	16700	Charleston-North Charleston, SC	07/10/2014
18580	Corpus Christi, TX	05/02/2014	17900	Columbia, SC	07/10/2014
27260	Jacksonville, FL	05/05/2014	24860	Greenville-Anderson-Mauldin, SC	07/10/2014
36540	Omaha-Council Bluffs, NE-IA	05/05/2014	34820	Myrtle Beach-Conway-North Myrtle Beach, SC-NC	07/10/2014
23104*	Fort Worth-Arlington, TX	05/05/2014	38900	Portland-Vancouver-Hillsboro, OR-WA	07/10/2014
44060	Spokane-Spokane Valley, WA	05/08/2014	12940	Baton Rouge, LA	07/11/2014
28140	Kansas City, MO-KS	05/09/2014	11100	Amarillo, TX	07/16/2014
42220	Santa Rosa, CA	05/12/2014	37100	Oxnard-Thousand Oaks-Ventura, CA	07/17/2014
41620	Salt Lake City, UT	05/27/2014	42020	San Luis Obispo-Paso Robles-Arroyo Grande, CA	07/17/2014
12420	Austin-Round Rock, TX	06/04/2014	25540	Hartford-West Hartford-East Hartford, CT	07/22/2014
36740	Orlando-Kissimmee-Sanford, FL	06/04/2014	21660	Eugene, OR	07/23/2014

Notes: Wherever UberX entry is specified at the Core Based Statistical Area (CBSA) Division level, these cases are denoted by a star in column (1). Otherwise CBSA codes and titles refer to Core Based Statistical Areas.

Table B3: Complete Uber Entry Dates 3 of 7

CBSA Area/Division Code (1)	CBSA Area/Division Title (2)	Date UberX Entered (3)	CBSA Area/Division Code (1)	CBSA Area/Division Title (2)	Date UberX Entered (3)
41420	Salem, OR	07/23/2014	30700	Lincoln, NE	08/28/2014
22420	Flint, MI	07/24/2014	37060	Oxford, MS	08/28/2014
24340	Grand Rapids-Wyoming, MI	07/24/2014	43780	South Bend-Mishawaka, IN-MI	08/28/2014
28020	Kalamazoo-Portage, MI	07/24/2014	45220	Tallahassee, FL	08/28/2014
29620	Lansing-East Lansing, MI	07/24/2014	46220	Tuscaloosa, AL	08/28/2014
24540	Greeley, CO	08/01/2014	47380	Waco, TX	08/28/2014
40060	Richmond, VA	08/06/2014	48620	Wichita, KS	08/28/2014
22744*	Fort Lauderdale-Pompano Beach-Deerfield Beach, FL	08/07/2014	19780	Des Moines-West Des Moines, IA	09/12/2014
48424*	West Palm Beach-Boca Raton-Delray Beach, FL	08/07/2014	11260	Anchorage, AK	09/18/2014
11700	Asheville, NC	08/21/2014	22380	Flagstaff, AZ	09/18/2014
15940	Canton-Massillon, OH	08/22/2014	14260	Boise City, ID	10/02/2014
14500	Boulder, CO	08/27/2014	38860	Portland-South Portland, ME	10/02/2014
22660	Fort Collins, CO	08/27/2014	49340	Worcester, MA-CT	10/06/2014
10420	Akron, OH	08/28/2014	15540	Burlington-South Burlington, VT	10/09/2014
12020	Athens-Clarke County, GA	08/28/2014	17860	Columbia, MO	10/09/2014
12220	Auburn-Opelika, AL	08/28/2014	24580	Green Bay, WI	10/16/2014
13980	Blacksburg-Christiansburg-Radford, VA	08/28/2014	31700	Manchester-Nashua, NH	10/17/2014
14020	Bloomington, IN	08/28/2014	16180	Carson City, NV	10/24/2014
16820	Charlottesville, VA	08/28/2014	29820	Las Vegas-Henderson-Paradise, NV	10/24/2014
17780	College Station-Bryan, TX	08/28/2014	39900	Reno, NV	10/24/2014
19380	Dayton, OH	08/28/2014	37964*	Philadelphia, PA	10/24/2014
22220	Fayetteville-Springdale-Rogers, AR-MO	08/28/2014	30780	Little Rock-North Little Rock-Conway, AR	11/06/2014
23540	Gainesville, FL	08/28/2014	40220	Roanoke, VA	11/06/2014
28940	Knoxville, TN	08/28/2014	16860	Chattanooga, TN-GA	11/13/2014
29200	Lafayette-West Lafayette, IN	08/28/2014	42140	Santa Fe, NM	11/19/2014

Notes: Wherever UberX entry is specified at the Core Based Statistical Area (CBSA) Division level, these cases are denoted by a star in column (1). Otherwise CBSA codes and titles refer to Core Based Statistical Areas.

Table B4: Complete Uber Entry Dates 4 of 7

CBSA Area/Division Code (1)	CBSA Area/Division Title (2)	Date UberX Entered (3)	CBSA Area/Division Code (1)	CBSA Area/Division Title (2)	Date UberX Entered (3)
47300	Visalia-Porterville, CA	12/01/2014	40420	Rockford, IL	02/15/2015
15980	Cape Coral-Fort Myers, FL	12/04/2014	29740	Las Cruces, NM	02/18/2015
16300	Cedar Rapids, IA	12/04/2014	25940	Hilton Head Island-Bluffton-Beaufort, SC	03/27/2015
18880	Crestview-Fort Walton Beach-Destin, FL	12/04/2014	29540	Lancaster, PA	03/27/2015
19660	Deltona-Daytona Beach-Ormond Beach, FL	12/04/2014	39740	Reading, PA	03/27/2015
28580	Key West, FL	12/04/2014	42340	Savannah, GA	03/27/2015
29460	Lakeland-Winter Haven, FL	12/04/2014	49620	York-Hanover, PA	03/27/2015
34940	Naples-Immokalee-Marco Island, FL	12/04/2014	12260	Augusta-Richmond County, GA-SC	04/06/2015
35840	North Port-Sarasota-Bradenton, FL	12/04/2014	21500	Erie, PA	04/10/2015
36100	Ocala, FL	12/04/2014	35380	New Orleans-Metairie, LA	04/16/2015
37340	Palm Bay-Melbourne-Titusville, FL	12/04/2014	29940	Lawrence, KS	04/23/2015
37460	Panama City, FL	12/04/2014	31740	Manhattan, KS	04/23/2015
37860	Pensacola-Ferry Pass-Brent, FL	12/04/2014	45820	Topeka, KS	04/23/2015
38940	Port St. Lucie, FL	12/04/2014	44140	Springfield, MA	04/24/2015
27140	Jackson, MS	12/11/2014	41540	Salisbury, MD-DE	04/27/2015
27980	Kahului-Wailuku-Lahaina, HI	12/18/2014	23060	Fort Wayne, IN	05/07/2015
44100	Springfield, IL	01/09/2015	23844*	Gary, IN	05/07/2015
25420	Harrisburg-Carlisle, PA	01/29/2015	22020	Fargo, ND-MN	05/12/2015
10900	Allentown-Bethlehem-Easton, PA-NJ	01/30/2015	39540	Racine, WI	05/21/2015
29180	Lafayette, LA	01/30/2015	12700	Barnstable Town, MA	05/22/2015
42540	Scranton–Wilkes-Barre–Hazleton, PA	02/06/2015	28620	Kill Devil Hills, NC	05/22/2015
44300	State College, PA	02/06/2015	12300	Augusta-Waterville, ME	05/25/2015
44660	Stillwater, OK	02/12/2015	17660	Coeur d'Alene, ID	06/04/2015
14010	Bloomington, IL	02/15/2015	26820	Idaho Falls, ID	06/04/2015
16580	Champaign-Urbana, IL	02/15/2015	38540	Pocatello, ID	06/04/2015

Notes: Wherever UberX entry is specified at the Core Based Statistical Area (CBSA) Division level, these cases are denoted by a star in column (1). Otherwise CBSA codes and titles refer to Core Based Statistical Areas.

Table B5: Complete Uber Entry Dates 5 of 7

CBSA Area/Division Code	CBSA Area/Division Title	Date UberX Entered	CBSA Area/Division Code	CBSA Area/Division Title	Date UberX Entered
(1)	(2)	(3)	(1)	(2)	(3)
46300	Twin Falls, ID	06/04/2015	37900	Peoria, IL	11/24/2015
33660	Mobile, AL	06/11/2015	22540	Fond du Lac, WI	11/25/2015
48864*	Wilmington, DE-MD-NJ	06/11/2015	27500	Janesville-Beloit, WI	11/25/2015
49740	Yuma, AZ	06/12/2015	36780	Oshkosh-Neenah, WI	11/25/2015
28660	Killeen-Temple, TX	07/02/2015	36260	Ogden-Clearfield, UT	12/18/2015
43900	Spartanburg, SC	07/16/2015	45340	Taos, NM	12/22/2015
19340	Davenport-Moline-Rock Island, IA-IL	07/21/2015	13820	Birmingham-Hoover, AL	12/28/2015
20100	Dover, DE	07/31/2015	24260	Grand Island, NE	02/01/2016
11180	Ames, IA	08/03/2015	13140	Beaumont-Port Arthur, TX	02/03/2016
10180	Abilene, TX	08/12/2015	33860	Montgomery, AL	02/04/2016
33260	Midland, TX	08/12/2015	17300	Clarksville, TN-KY	03/03/2016
36220	Odessa, TX	08/12/2015	26620	Huntsville, AL	03/04/2016
14540	Bowling Green, KY	08/27/2015	30340	Lewiston-Auburn, ME	03/21/2016
22900	Fort Smith, AR-OK	09/01/2015	12620	Bangor, ME	03/23/2016
39340	Provo-Orem, UT	09/03/2015	12740	Barre, VT	03/26/2016
11540	Appleton, WI	09/10/2015	26980	Iowa City, IA	04/28/2016
41180	St. Louis, MO-IL	09/18/2015	31420	Macon-Bibb County, GA	05/10/2016
14740	Bremerton-Silverdale, WA	09/30/2015	47580	Warner Robins, GA	05/10/2016
24300	Grand Junction, CO	10/06/2015	41460	Salina, KS	05/21/2016
17020	Chico, CA	10/08/2015	18180	Concord, NH	06/01/2016
19060	Cumberland, MD-WV	10/20/2015	49660	Youngstown-Warren-Boardman, OH-PA	06/23/2016
25180	Hagerstown-Martinsburg, MD-WV	10/20/2015	25060	Gulfport-Biloxi-Pascagoula, MS	07/01/2016
25500	Harrisonburg, VA	10/23/2015	25620	Hattiesburg, MS	07/01/2016
15260	Brunswick, GA	11/06/2015	36500	Olympia-Tumwater, WA	07/15/2016
13380	Bellingham, WA	11/11/2015	16620	Charleston, WV	07/19/2016

Notes: Wherever UberX entry is specified at the Core Based Statistical Area (CBSA) Division level, these cases are denoted by a star in column (1). Otherwise CBSA codes and titles refer to Core Based Statistical Areas.

Table B6: Complete Uber Entry Dates 6 of 7

CBSA Area/Division Code	CBSA Area/Division Title	Date UberX Entered	CBSA Area/Division Code	CBSA Area/Division Title	Date UberX Entered
(1)	(2)	(3)	(1)	(2)	(3)
26580	Huntington-Ashland, WV-KY-OH	07/19/2016	16060	Carbondale-Marion, IL	03/02/2017
28060	Kalispell, MT	08/01/2016	20740	Eau Claire, WI	03/02/2017
33540	Missoula, MT	08/01/2016	24220	Grand Forks, ND-MN	03/02/2017
24500	Great Falls, MT	08/02/2016	29100	La Crosse-Onalaska, WI-MN	03/02/2017
15580	Butte-Silver Bow, MT	08/03/2016	31860	Mankato-North Mankato, MN	03/02/2017
25740	Helena, MT	08/03/2016	40340	Rochester, MN	03/02/2017
14580	Bozeman, MT	08/04/2016	40980	Saginaw, MI	03/02/2017
13740	Billings, MT	08/05/2016	41060	St. Cloud, MN	03/02/2017
27740	Johnson City, TN	08/19/2016	48140	Wausau, WI	03/02/2017
28700	Kingsport-Bristol-Bristol, TN-VA	08/19/2016	16220	Casper, WY	03/03/2017
48300	Wenatchee, WA	08/19/2016	16940	Cheyenne, WY	03/03/2017
17980	Columbus, GA-AL	09/20/2016	28180	Kapaa, HI	03/10/2017
46340	Tyler, TX	09/22/2016	17200	Claremont-Lebanon, NH-VT	03/22/2017
44180	Springfield, MO	11/17/2016	30020	Lawton, OK	03/22/2017
25860	Hickory-Lenoir-Morganton, NC	12/15/2016	20220	Dubuque, IA	04/01/2017
28420	Kennewick-Richland, WA	12/15/2016	43580	Sioux City, IA-NE-SD	04/01/2017
49420	Yakima, WA	12/16/2016	47940	Waterloo-Cedar Falls, IA	04/01/2017
14380	Boone, NC	01/13/2017	20260	Duluth, MN-WI	05/01/2017
40860	Rutland, VT	01/20/2017	10500	Albany, GA	05/17/2017
21780	Evansville, IN-KY	01/25/2017	46660	Valdosta, GA	05/17/2017
30860	Logan, UT-ID	02/01/2017	27940	Juneau, AK	06/19/2017
45460	Terre Haute, IN	02/28/2017	21820	Fairbanks, AK	06/21/2017
25900	Hilo, HI	03/01/2017	32580	McAllen-Edinburg-Mission, TX	06/27/2017
27100	Jackson, MI	03/01/2017	10580	Albany-Schenectady-Troy, NY	06/29/2017
13900	Bismarck, ND	03/02/2017	13780	Binghamton, NY	06/29/2017

Notes: Wherever UberX entry is specified at the Core Based Statistical Area (CBSA) Division level, these cases are denoted by a star in column (1). Otherwise CBSA codes and titles refer to Core Based Statistical Areas.

Table B7: Complete Uber Entry Dates 7 of 7

CBSA Area/Division Code	CBSA Area/Division Title	Date UberX Entered	CBSA Area/Division Code	CBSA Area/Division Title	Date UberX Entered
(1)	(2)	(3)	(1)	(2)	(3)
15380	Buffalo-Cheektowaga-Niagara Falls, NY	06/29/2017	43340	Shreveport-Bossier City, LA	02/15/2018
21300	Elmira, NY	06/29/2017	10100	Aberdeen, SD	06/20/2019
24020	Glens Falls, NY	06/29/2017	39660	Rapid City, SD	06/20/2019
27060	Ithaca, NY	06/29/2017	43620	Sioux Falls, SD	06/20/2019
40380	Rochester, NY	06/29/2017			
45060	Syracuse, NY	06/29/2017			
46540	Utica-Rome, NY	06/29/2017			
29700	Laredo, TX	07/12/2017			
20580	Eagle Pass, TX	07/13/2017			
27860	Jonesboro, AR	08/01/2017			
41660	San Angelo, TX	08/04/2017			
18060	Columbus, MS	08/18/2017			
32940	Meridian, MS	08/18/2017			
44260	Starkville, MS	08/18/2017			
48660	Wichita Falls, TX	08/22/2017			
18700	Corvallis, OR	09/20/2017			
33740	Monroe, LA	09/20/2017			
35740	Norfolk, NE	09/23/2017			
45500	Texarkana, TX-AR	09/26/2017			
34860	Nacogdoches, TX	09/27/2017			
39420	Pullman, WA	09/29/2017			
45900	Traverse City, MI	10/17/2017			
32780	Medford, OR	12/01/2017			
22500	Florence, SC	12/08/2017			
13220	Beckley, WV	12/24/2017			

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