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 healthcare. Event-studies show parallel trends in outcomes before UberX entry and results are robust to numerous sensitivity checks.

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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 recent advent of UberHealth suggests that healthcare providers often use ridesharing services to help transport patients to and from appointments. According to UberHealth, introduced to United States 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 patients report that they do not receive sufficient care (Substance Abuse and Mental Health Services Administration, 2023). Given

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[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.

the social costs of substance use disorder, estimated to be $682 billion per year (Caulkins 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.[4] 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.[5] 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

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[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]UberX first launched in New York City in late 2012, and subsequently rolled out across the U.S. The Uber "black car" service was launched in 2011 in New York City, San Francisco, and perhaps a few other cities, where the company recruited limousine drivers. This service was marketed as luxury transportation and targeted towards higher income and business consumers. The company transitioned the name of that service to UberBlack once Uber rolled out UberX as direct competition to traditional taxis (e.g., "A Status Symbol Moves Down Market: The Context for Uber's Lower-Priced Launch" https://allthingsd.com/20120702/a-status-symbol-moves-down-market-whats-behind-the-uberx-launch/; website last accessed 9/7/2024).

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

end of 2018.[6] 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 when treatment adoption is staggered across units.

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 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. Note that we do not mean to imply that intensive outpatient treatment is clinically superior. Our estimates are merely consistent with the idea that transportation constraints affect treatment modality decisions for those seeking care for a substance use disorder.

Primarily, we see the effects concentrated among patients 18-34 years old. Smith (2016) reports 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 finds that 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

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[6]According to the U.S. Census Bureau, CBSAs "consist of the county or counties (or equivalent entities) associated with at least one core (urban area) of at least 10,000 population, plus adjacent counties having a high degree of social and economic integration with the core as measured through commuting ties" https://www.census.gov/programs-surveys/metro-micro/about/glossary.html, website last accessed 10/7/2024.

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.[7] These patterns again support the idea that UberX entry is 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 support the parallel trends assumption, and show that the treatment effects increase over time, a pattern that is consistent with the UberX market growing as more riders and drivers use the platform (Bagchi, 2018; Hall and Krueger, 2018; Hall et al., 2018).

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; Deza et al., 2023;

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

Bradford and Maclean, 2024). 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.[8] 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 adulthood (Kessler et al., 2005), likely from a combination of environment and genetics. These disorders negatively impact health, employment, and other socioeconomic outcomes.

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[8]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.

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.[9] 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).[10] 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 spheres of their lives. While these services vary across treatment centers, they can include

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[9]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).

[10]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.

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.[11] 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 TEDS. Every year, TEDS gathers information from specialized substance use disorder 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).[12]

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[11]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.

[12]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. 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 outpatient 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.[13] 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 outpatient 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 4.65 admissions of any type per 1,000 population per year, where non-intensive outpatient admissions are the most common subcategory at 2.03 per year (44% of the total), followed by detoxification at 1.15, residential at 0.86, and intensive outpatient at 0.6. 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

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

maps of CBSAs with available TEDS data that ever experienced a known 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, UberX's main competition. Lyft entry typically occurred after UberX entry and Lyft had a significantly smaller market share during our sample period.[14] We suspect that, all else equal, any measurement error in treatment timing from omitting Lyft entry information would likely attenuate our coefficient 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 main design compares treatment admissions in CBSA-years where UberX has entered (sometime between 2012 and 2018, depending on the CBSA) to CBSA-years where UberX has not yet entered but does by 2019. 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.[15] 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 our preferred specification, we include the

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

[15]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.

time-varying per-capita number of substance use disorder treatment centers in the CBSA, denoted as the X_{jt} term. Showing estimates where we include and exclude this covariate helps alleviate the concern that UberX entry may be correlated with the emergence of new treatment centers.[16] Our preferred specification weights observations by CBSA population.

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 CBSAs that UberX enters would be parallel to the trend in CBSAs that UberX has not yet entered. That assumption is untestable as counterfactuals are not observed, 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 a standard two-way fixed effects (TWFE) regression to estimate equations 1 and 2 creates the potential for heterogeneous and dynamic treatment effect bias (Baker et al., 2022).

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[16]Indeed, we find little to no difference in our estimates presented in Table 1.

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 imposes a constant treatment effect and would therefore be misspecified. This type of misspecification can bias estimates of β in either direction. Using the Goodman-Bacon (2021) decomposition procedure to test for such issues (see Appendix section A.4), we find that 43% of the two-by-two difference-in-differences that comprise the two-way fixed effects estimates of the average treatment on the treated (ATT) involve comparisons between later treated and earlier treated areas. These are known as "forbidden" comparisons because they can create a treatment effect bias (Borusyak et al., 2024). Event-studies are also subject to these concerns (Sun and Abraham, 2021).

To avoid this bias, we choose the two-step difference-in-differences estimator proposed by Gardner (2022) from the new class of robust difference-in-differences estimators.[17] This approach uses the untreated or not-yet-treated areas to estimate the relationships between time-varying covariates and fixed effects.[18] The first step uses those estimates to residualize the outcomes (i.e., treatment admissions) for both treated and untreated observations. In the second step, the residualized outcomes are regressed on the treatment variable (using treated and untreated observations). We select the Gardner (2022) approach for several reasons. First, it allows us to control for time-varying covariates (e.g., number of substance use disorder treatment centers) and is robust to treatment effect heterogeneity that is correlated with covariates (Powell, 2021). Second, the Gardner approach relies on regression, which is a familiar concept to most economists and applied researchers. Third, the standard errors are estimated within a generalized method of moments framework, and account for both the imputation in the first step and within-CBSA clustering over time. In the appendix, we

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[17]Some of the other estimators in this class include Borusyak et al. (2024), Callaway and Sant'Anna (2021), de Chaisemartin and d'Haultfoeuille (2020), and the stacked approach from Cengiz et al. (2019).

[18]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.

show that the Borusyak et al. (2024), Callaway and Sant'Anna (2021), and other estimators produce nearly identical coefficient estimates.

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 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,[19] 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,

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[19]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.

2022). Thus, the offsetting effects on intensive and non-intensive outpatient admissions suggest 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 to address the concern that UberX entry may be correlated with the emergence of new treatment centers, we find very similar 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). Additionally, when we regress the number of centers per capita on UberX entry into a CBSA using equation 1, we find no evidence that UberX entry predicts the number of centers per capita ($\hat{\beta} = -0.0010$, $\sigma_{\hat{\beta}} = 0.0007$). Throughout the rest of our analyses, we therefore use the Panel B specification as our preferred specification.

We further support a causal interpretation of our estimates 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-step 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 UberX driver-partners within cities, 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 mirrors the trend in public interest towards UberX over time, as evidenced by Google Trends data (see Figure 1 of Hall et al., 2018).[20]

In Appendix Figure A2 we probe 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 one year, and include an extended set of controls (e.g., state-by-year fixed effects). We also examine TEDS discharge (versus 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 did not experience an UberX entry. Notably, our main approach of omitting areas where UberX does not enter aligns with the existing literature; such areas are unlikely to provide valid comparisons to areas where UberX entered. Further, it is more accurate to characterize "untreated" areas as those for which the timing of UberX entry is undetermined and thus should not be included in our sample.[21] As an additional robustness check, 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.

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[20]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.

[21]Excluding areas where UberX does not enter 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 had lower population.

While not shown in the figure, each coefficient estimate in the "leave-one-out" analyses is significant at the 5% level or greater.

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 UberX and smartphone users during the sample period (Smith, 2016). We see this pattern of results as evidence that supports a causal interpretation of our findings. We also observe larger effects among men and minority groups.

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. 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.[22] 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. 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

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

impact on people and areas where access to care was more challenging prior to the entry of ridesharing services.

In Figure 4, we examine heterogeneity by criminal justice system referrals, prior treatment history (no treatment versus previous treatment), and whether there was a co-occurring mental health disorder at admission. Starting with criminal justice system referrals, UberX entry into a CBSA may lead to changes in sentencing patterns, as judges, prosecutors, defense attorneys, defendants, and probation officers may be more likely to suggest transportation-intensive treatment at any point in the criminal justice process.[23] In fact, our evidence suggests that criminal justice referrals drive the main estimates. Turning to heterogeneity by prior treatment status, we see similar evidence of substitution between intensive and non-intensive treatment. Finally, 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 among those with a mental health disorder. The smaller effect size is appropriate given this is a subset of all admissions and our estimates are per 1,000 population. While not included in Figure 4, we also examined whether UberX led to any changes in medications used to treat opioid disorders (MOUD). We find that 35% of the overall reduction in NI-OP admissions are cases involving MOUD, and that 100% of the overall increase in I-OP admissions are cases that *do not* involve MOUD. This pattern is perhaps unsurprising, as MOUD is used in only 3% of observed pre-treatment I-OP admissions. One possibility is that individuals opt for intensive outpatient treatment without MOUD, rather than non-intensive treatment using MOUD. Another possibility is that new I-OP patients still receive MOUD, but do so

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[23]According to Belenko et al. (2013), "there are several stages in criminal case processing at which linkages to treatment are possible." These stages include the initial hearing where charges are presented, pretrial diversion, the trial or plea bargain stage, or after a defendant is sentenced to probation. Diversion to drug courts is also possible, though these comprise a very small share of admissions in our TEDS sample (0.8%). In addition, new arrestees often have the opportunity to suspend their cases while they attend treatment, and successful completion can result in charge dismissal, reduction of charges, or reducing sentence severity (Belenko et al., 2013). Such diversion programs are usually controlled by prosecutors, who are ultimately responsible for screening eligible cases and monitoring progress (Belenko et al., 2013).

at separate (non-TEDS) facilities such as private clinician offices where buprenorphine and naltrexone are generally obtained.[24]

In Appendix Table A3, we report coefficient estimates using procedures robust to heterogeneous treatment effects proposed by Cengiz et al. (2019), Borusyak et al. (2024), de Chaisemartin and d'Haultfoeuille (2020), and Callaway and Sant'Anna (2021). The pattern of coefficient estimates is very similar to our main findings using the Gardner (2022) estimator. We also provide coefficient estimates using two-way fixed effects regression to illustrate the bias introduced by treatment effect heterogeneity along with the staggered rollout of UberX. Figure A5 provides the corresponding event-study figures. As additional appendix items, to further motivate the use of a difference-in-differences estimator that is robust to heterogeneous treatment timing bias, we provide the Goodman-Bacon (2021) decomposition for intensive and non-intensive outpatient admissions (Figure A4). The decomposition reveals that 43% of the comparisons are of the "forbidden" type (using earlier treated areas as a comparison group for later treated areas), and that those "forbidden comparisons" bias the two-way fixed effects coefficient estimates toward zero. In the appendix, we also provide event-studies and difference-in-differences estimates using the Gardner (2022) estimator by treatment cohort (Figures A6 and A7).[25] We see similar patterns across cohorts, with somewhat larger effects for later-treated cohorts. Importantly, these figures provide further evidence to support our parallel trends assumption across cohorts. Finally, Figure A8 shows trends in admissions by UberX entry cohort leading up to the first UberX entry in 2012 to show that trends in our outcomes of interest are not predictive of eventual UberX entry.

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[24]This treatment setting is in contrast to methadone, which can only be obtained in federal certified opioid treatment programs.

[25]The cohorts are grouped by UberX entries occurring in 2012/2013, 2014, and 2015/2016. We cannot provide coefficient estimates for the 2017 or 2018 entry cohort as our estimation sample ends in 2018.

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 use disorder does not receive treatment for over a decade 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.[26] We also do not observe a net increase in admissions from 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.[27]

A related concern may arise based on earlier studies that find reductions in rates of driving under the influence (DUI) (e.g., Dills and Mulholland, 2018; Zhou, 2020). That is, if UberX reduces DUIs, the entry of UberX into a CBSA might reduce DUI-related treatment referrals, and thus free up centers' capacity to provide intensive treatment services. In examining this possibility, we find a small *positive* effect of UberX on DUI-related criminal justice referrals

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[26]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.

[27]Non-intensive outpatient treatment is disproportionately common among those referred through the criminal justice system. Over our study period, 62.9% of criminal justice system referrals occur in non-intensive outpatient settings while the share is 36.5% among non-criminal justice system referrals.

to *both* intensive and non-intensive outpatient treatment.[28] Moreover, DUI-related referrals comprise just 2.5% of our estimation sample, and the most common setting for DUI-related referrals is non-intensive outpatient. Taken together, these factors suggest that DUI-related changes in capacity do not explain our main results. To address capacity considerations more broadly, we present coefficient estimates from a regression where the outcome of interest is the share of admissions where patients had to wait more than two weeks or more than 30 days to start receiving care (Appendix Table A4). Here we find no statistically significant effect on wait times.

Finally, in Appendix Table A5, 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 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

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[28]Detailed results are available upon request. We find an increase in DUI-related NI-OP of 0.04 per 1,000 per year, which is statistically significant at the 10% level, and an increase in DUI-related I-OP of 0.15 per 1,000 per year, which is statistically significant at the 1% level.

without an increase in total admissions. Intensive care is potentially more appropriate for some 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 Two-Stage Difference-in-Differences: Treatment Episode Data Set 2008-2018
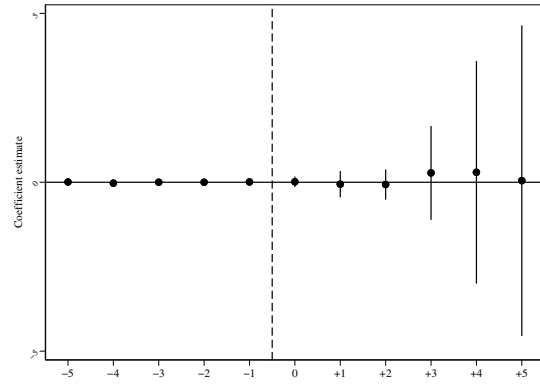
	Total	Detoxifica-tion	Residential	Intensive Outpatient	Non-intensive Outpatient
	(1)	(2)	(3)	(4)	(5)
Panel A: Core Based Statistical Area and Year Fixed Effects Only					
UberX entry	0.33	0.11	0.14	0.69***	-0.62**
	(0.75)	(0.73)	(0.11)	(0.22)	(0.27)
Panel B: Controlling for Core Based Statistical Area and Year Fixed Effects and Number of Treatment Centers Per Capita (Main Sample & Specification)					
UberX entry	0.38	0.08	0.15	0.68***	-0.54**
	(0.78)	(0.71)	(0.11)	(0.21)	(0.23)
Pre-treatment mean	4.78	1.10	0.87	0.61	2.20
Core Based Statistical Areas	265	265	265	265	265
Treated Core Based Statistical Areas	260	260	260	260	260
Years	11	11	11	11	11
Observations	2801	2801	2801	2801	2801

Notes: In Panel A, the regression specification includes Core Based Statistical Area fixed effects and year fixed effects. We then add a control for the number of substance use disorder treatment centers per capita in Panel B, and use this as our base specification for our event-studies and heterogeneity analyses. The estimation sample includes only Core Based Statistical Areas where UberX enters by 2019. Data are the Treatment Episode Data Set 2008 to 2018. The unit of observation is a Core Based Statistical Area in a year. Data are weighted by the Core Based Statistical Area population. Standard errors are clustered at the Core Based Statistical Area level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
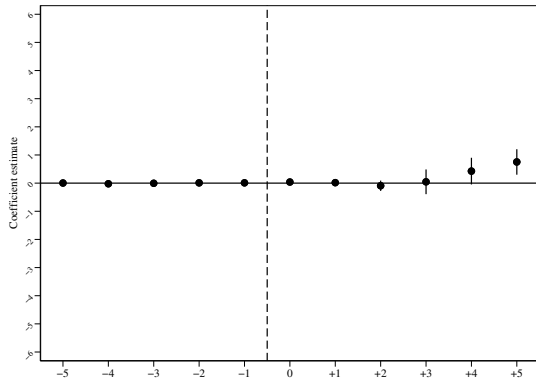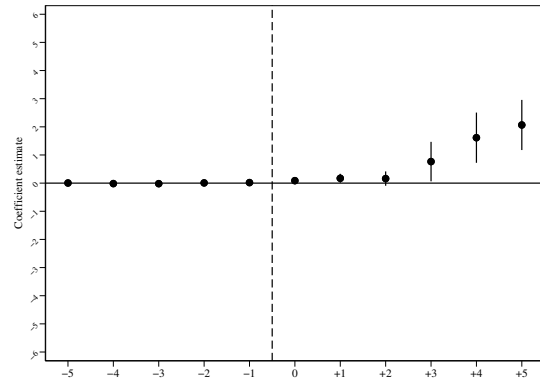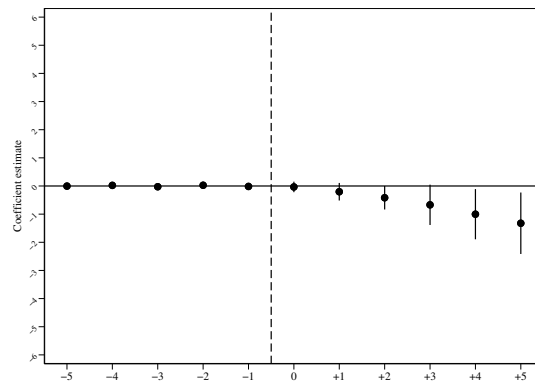
Figure 1: Event-studies
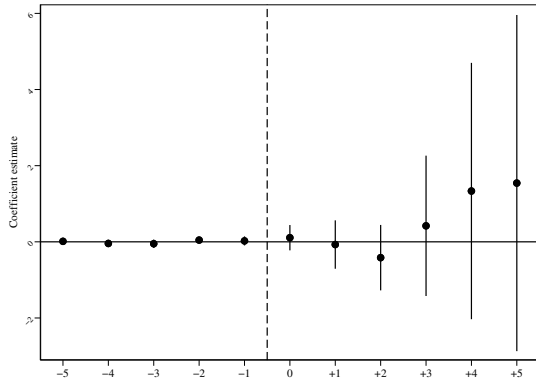
(a) Total Admissions

(b) Detoxification

(c) Residential

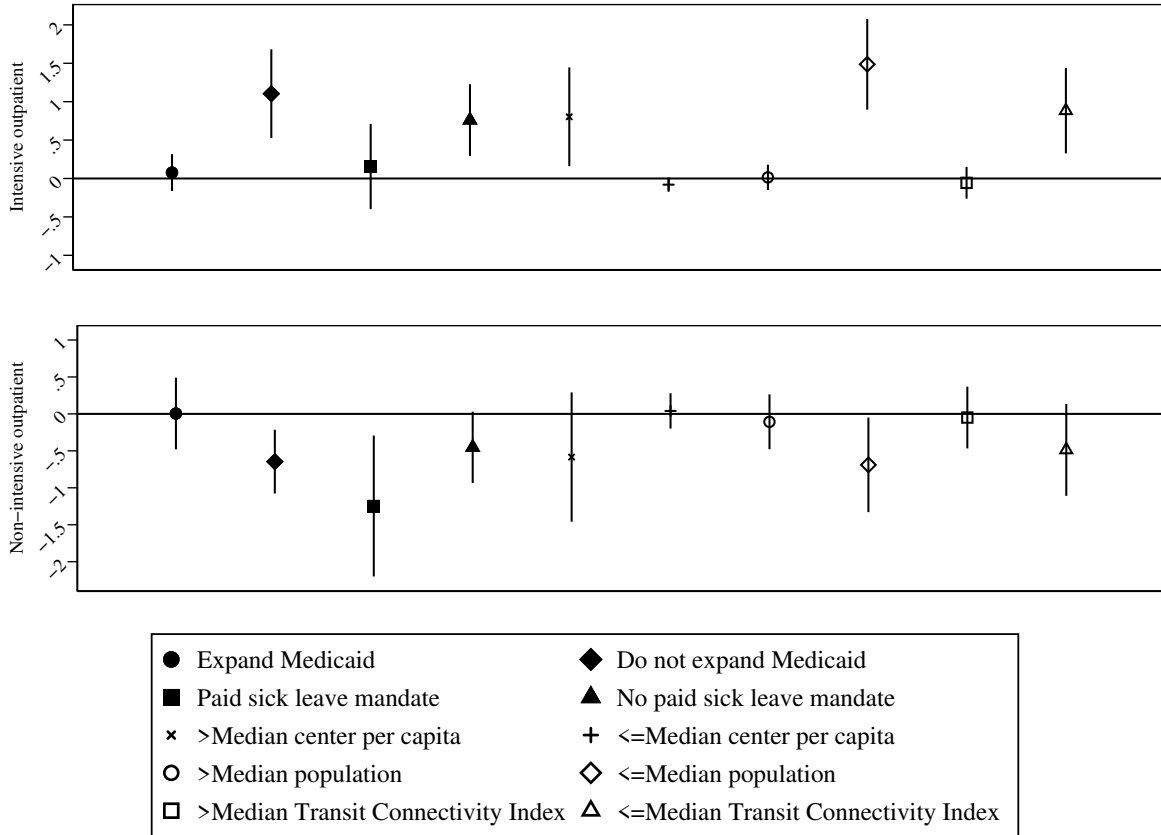(d) Intensive Outpatient

(e) Non-intensive Outpatient

Notes: These event-study figures show the effect of UberX entry on the noted outcome per 1,000 population. The estimation sample includes only Core Based Statistical Areas where UberX enters by 2019. Data are the Treatment Episode Data Set 2008 to 2018. All regressions estimated with the Gardner (2022) two-step difference-in-differences procedure and control for Core Based Statistical Areas' number of substance use disorder treatment centers per 1,000 residents, Core Based Statistical Area fixed effects, and year fixed effects. The unit of observation is a Core Based Statistical Area in a year. Data are weighted by the Core Based Statistical Area population. 95% confidence intervals that account for within-Core Based Statistical Area clustering are reported with vertical lines.

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Figure 2: Demographic Heterogeneity of Intensive versus Non-Intensive Outpatient Effects
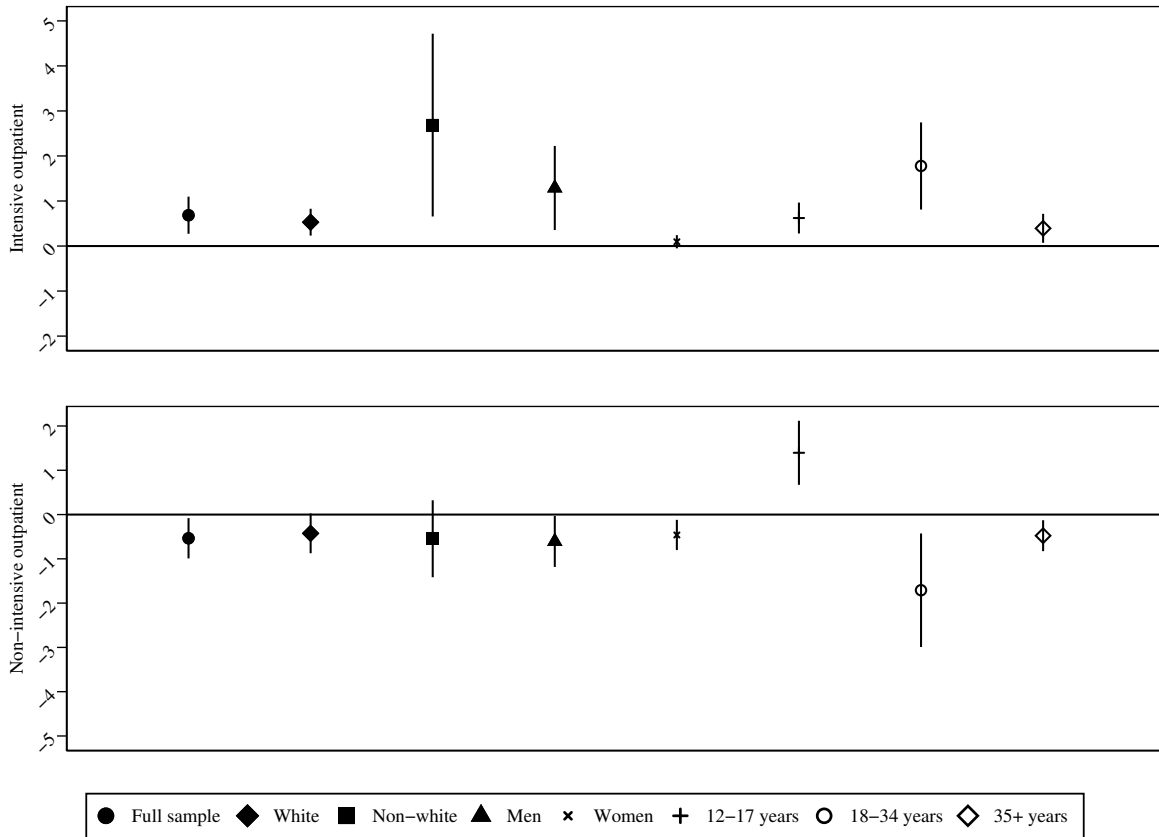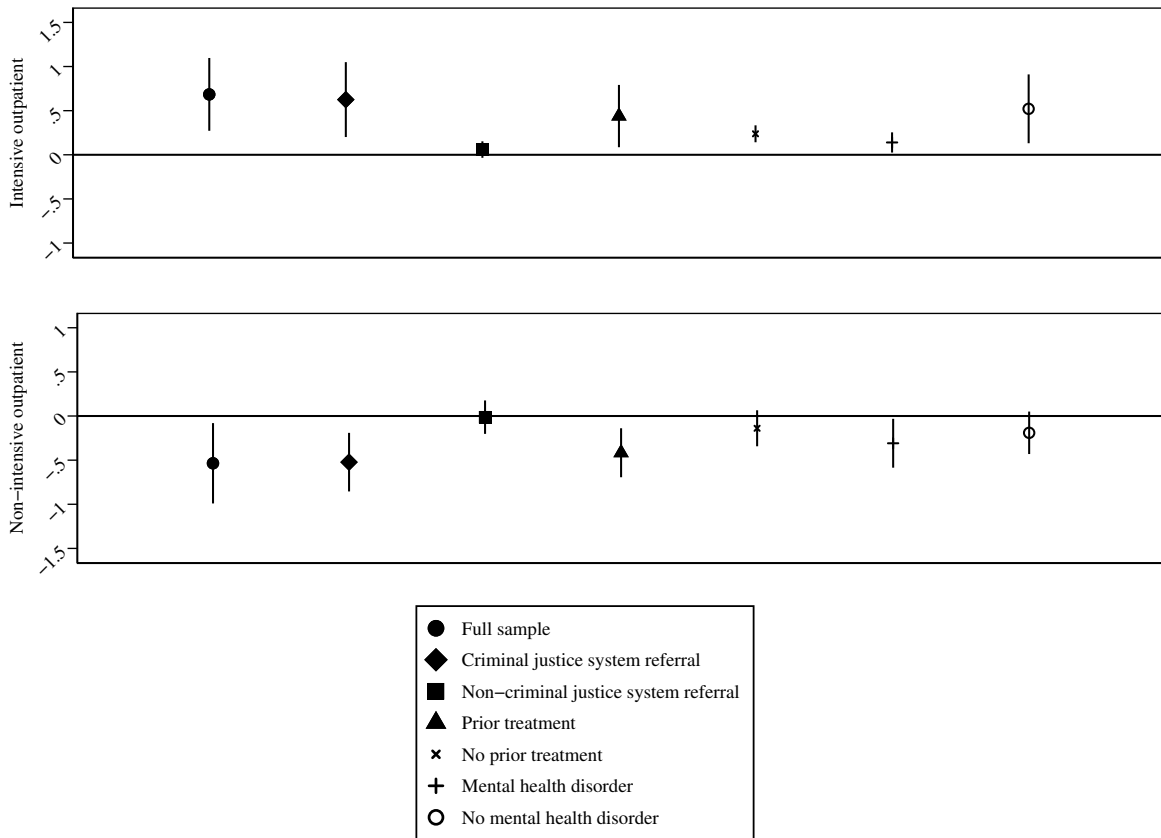

Notes: We report the effect of UberX entry on the intensive versus non-intensive outpatient changes per 1,000 population for various demographic subgroups. The legend explains the relevant subgroup sample restriction that we use to produce the coefficient estimate. These include race, sex, and age subgroups.The estimation sample includes only Core Based Statistical Areas where UberX enters by 2019. Data are the Treatment Episode Data Set 2008 to 2018. All regressions estimated with the Gardner (2022) two-step difference-in-differences procedure and control for Core Based Statistical Areas' number of substance use disorder treatment centers per 1,000 residents, Core Based Statistical Area fixed effects, and year fixed effects. The unit of observation is a Core Based Statistical Area in a year. Data are weighted by the Core Based Statistical Area population. 95% confidence intervals that account for within-Core Based Statistical Area clustering are reported with vertical lines.

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

Notes: We report the effect of UberX entry on the intensive versus non-intensive outpatient changes per 1,000 population by area characteristics. The legend explains the relevant sample restriction that produces the coefficient estimate. These include states that expanded Medicaid eligibility under the Affordable Care Act provisions versus those that did not; and paid sick leave versus non-paid sick leave, referring to the presence of paid sick leave mandates at the state level. The remaining coefficient estimates capture the treatment effect of UberX entry in Core Based Statistical Areas with above versus below median treatment centers per capita, population, and transportation connectivity (The Center for Neighborhood Technology, 2024).The estimation sample includes only Core Based Statistical Areas where UberX enters by 2019. Data are the Treatment Episode Data Set 2008 to 2018. All regressions estimated with the Gardner (2022) two-step difference-in-differences procedure and control for Core Based Statistical Areas' number of substance use disorder treatment centers per 1,000 residents, Core Based Statistical Area fixed effects, and year fixed effects. The unit of observation is a Core Based Statistical Area in a year. Data are weighted by the Core Based Statistical Area population. 95% confidence intervals that account for within-Core Based Statistical Area clustering are reported with vertical lines.

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


Notes: We report the effect of UberX entry on the intensive versus non-intensive outpatient admissions per 1,000 population by clinical characteristics. The legend explains the relevant sample restriction that produces the coefficient estimate. These include sub-sample analyses focusing on whether the admission is related to the criminal justice system, prior treatment versus not having had prior treatment, and being admitted with a co-occurring mental health disorder. The estimation sample includes only Core Based Statistical Areas where UberX enters by 2019. Data are the Treatment Episode Data Set 2008 to 2018. All regressions estimated with the Gardner (2022) two-step difference-in-differences procedure and control for Core Based Statistical Areas' number of substance use disorder treatment centers per 1,000 residents, Core Based Statistical Area fixed effects, and year fixed effects. The unit of observation is a Core Based Statistical Area in a year. Data are weighted by the Core Based Statistical Area population. 95% confidence intervals that account for within-Core Based Statistical Area clustering are reported with vertical lines.

Appendix A   Additional Figures and Tables

A.1   Trends in Substance Use Disorder Treatment Admissions Over Time

In Figure A1 we show the trends in admissions per 1,000 residents to different types of substance use disorder treatment over time.

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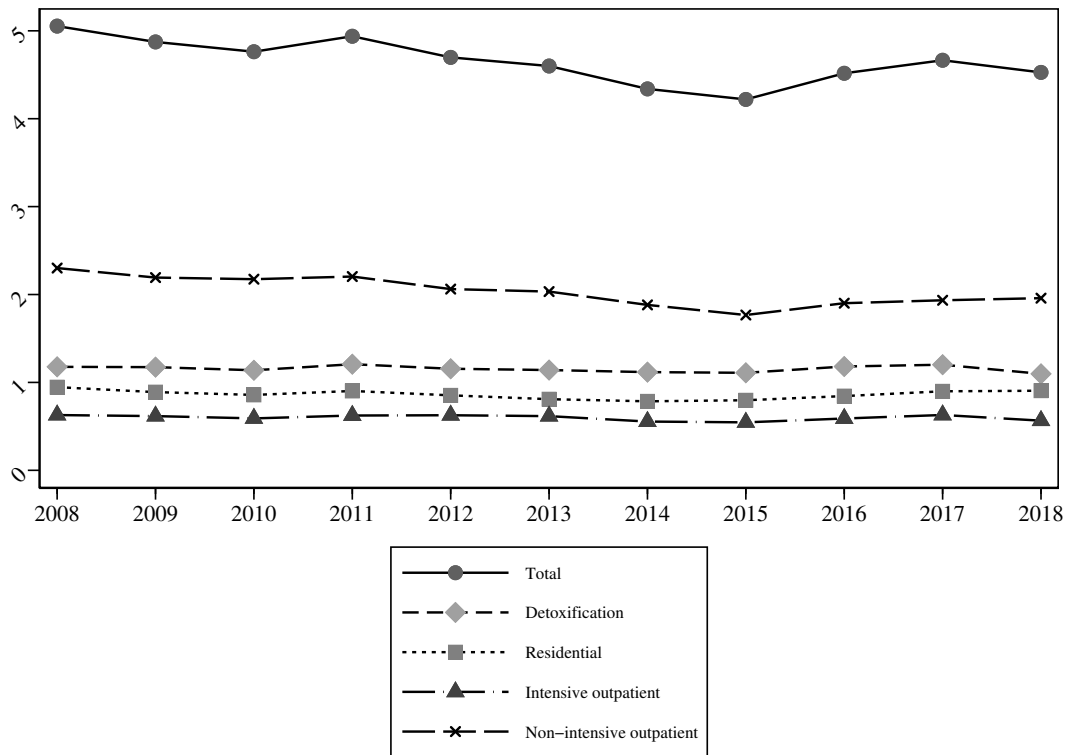

Notes: Treatment Episode Data Set 2008-2018. The unit of observation is a year. Data are weighted by the Core Based Statistical Area population.

A.2 Robustness Checks

In Figure A2 we present the robustness of our intensive and non-intensive outpatient ("I-OP" and "NI-OP") admissions coefficient 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.
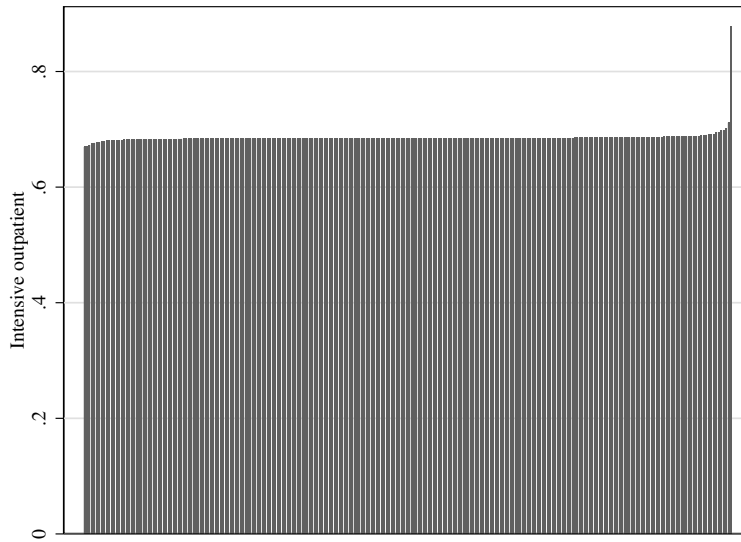
In Figure A3, we present an ordered histogram of coefficient estimates for intensive and then non-intensive substance use disorder treatment where we sequentially remove the data for one CBSA from our sample, repeat our estimates, store the coefficients, and then restore that CBSA to the sample before removing data related to the next CBSA. We then plot all of the coefficient estimates 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. When we focus on intensive outpatient admissions, excluding the Shreveport-Bossier City, LA CBSA yields the largest (in absolute value) coefficient estimate, while dropping the Bridgeport-Stamford-Norwalk, CT CBSA yields the smallest (in absolute value) 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.

Figure A2: Robustness of Intensive versus Non-Intensive Outpatient Effects
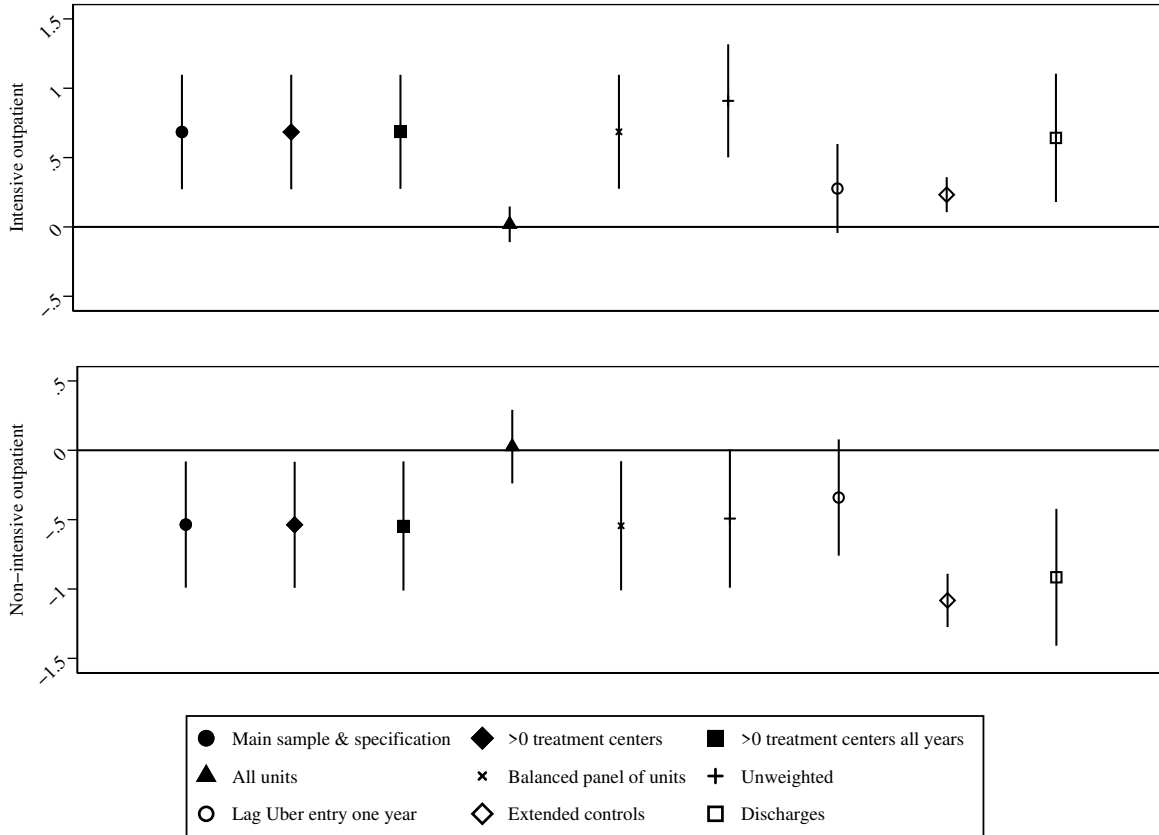
Notes: We report the effect of UberX entry on intensive versus non-intensive outpatient changes per 1,000 population as a function of various sample and data restrictions and choices. Estimation uses the Gardner (2022) two-step procedure and the Treatment Episode Data Set from 2008-2018. The legend summarizes 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 treatment centers, and then the more restrictive > 0 treatment centers all years), expanding the sample to include all Core Based Statistical Areas, a balanced panel, showing estimates without weighting, lagging UberX entry by one year, including an extended set of controls that includes state-by-year fixed effects and transit connectivity, and examining the change in treatment discharges. 95% confidence intervals that account for within-Core Based Statistical Area clustering are reported with vertical lines. Unless noted otherwise, we control for Core Based Statistical Areas' number of substance use disorder treatment centers per 1,000 residents, Core Based Statistical Area fixed effects, and year fixed effects in each specification. The unit of observation is a Core Based Statistical Area in a year. Data are weighted by the Core Based Statistical Area population.

Figure A3: Leave-one-out Analyses

(a) Intensive Treatment
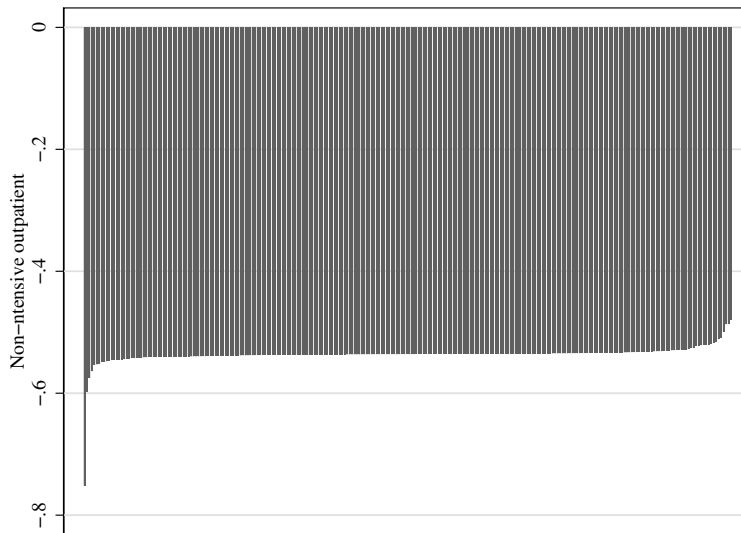
(b) Non-intensive Treatment

Notes: Figures show an ordered histogram of coefficient estimates for intensive non-intensive substance use disorder treatment where we remove one Core Based Statistical Area from our sample at a time. Estimation uses the Gardner (2022) two-step procedure and the Treatment Episode Data Set from 2008-2018. Plotting the standard errors of each estimate is not possible given the number of Core Based Statistical Areas in our sample. However, we note that all coefficient estimates are statistically significant at the 5% level or greater. We control for Core Based Statistical Areas' number of substance use disorder treatment centers per 1,000 residents, Core Based Statistical Area fixed effects, and year fixed effects in each specification. The unit of observation is a Core Based Statistical Area in a year. Data are weighted by the Core Based Statistical Area population.

A.3 Summary Statistics

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% versus 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.

[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.

Table A1: Demographics of Patients in Substance Use Disorder Treatment: Treatment Episode Data Set 2008-2018

Variable:	Proportion
12 to 17 years	0.057
18 to 34 years	0.50
35 to 64 years	0.44
65 or more years	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	7459577

Note: Data from the Treatment Episode Data Set 2008-2018. The unit of observation is a patient in a Core Based Statistical Area in a year. Data are unweighted.

Table A2: Summary Statistics for Treatment Episode Data Set 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
Observations	2801

Note: The unit of observation is a Core Based Statistical Area in a year. Admissions counts per capita are weighted by the Core Based Statistical Area population. Data sources: Treatment Episode Data Set, County Business Patterns, and National Cancer Institute Surveillance, Epidemiology, and End Results population data from ever-treated Core Based Statistical Areas from 2008-2018.
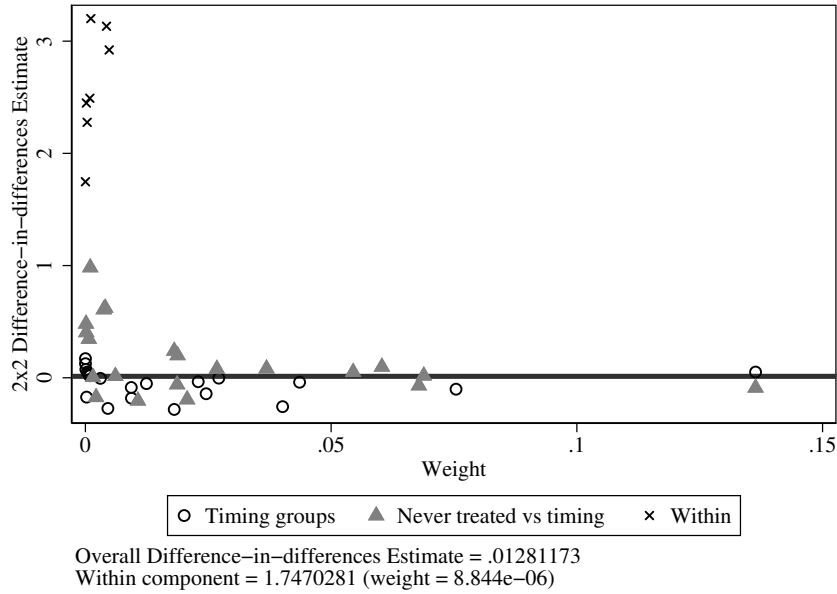
A.4 Staggered Timing and Alternate Estimators

As we explain in the main text, we are concerned about treatment timing bias (Baker et al., 2022) due to the staggered UberX rollout. We use the Gardner (2022) two-step estimator for our main specification. In Table A3, we present two-way fixed effects coefficient estimates to illustrate the size of the bias created by staggered treatment timing. We then present Borusyak et al. (2024), Callaway and Sant'Anna (2021), de Chaisemartin and d'Haultfoeuille (2020), and "stacked" difference-in-difference estimates (Cengiz et al., 2019). Stacked difference-in-differences specifications include cohort-specific CBSA and year fixed effects. In those estimates, we see a consistent pattern with increases in admissions to intensive outpatient treatment coupled with declines in non-intensive outpatient treatment.
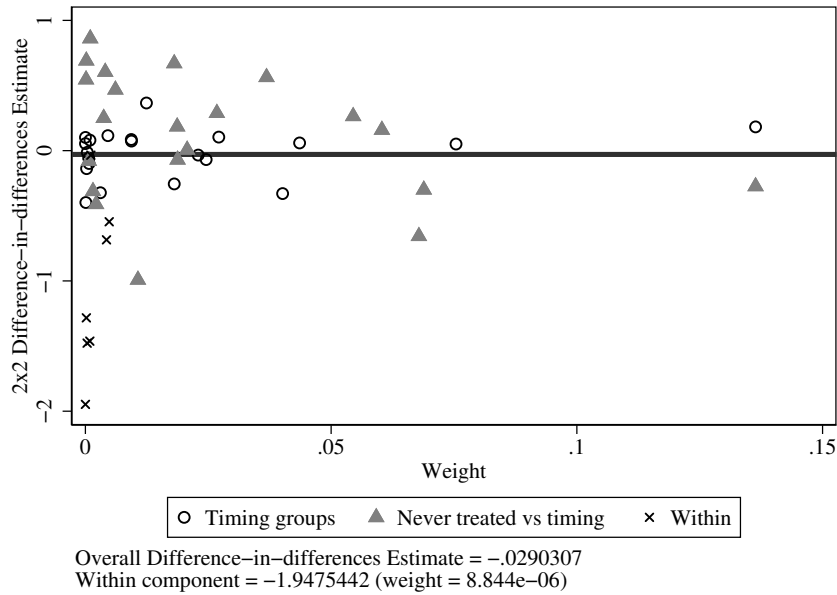
To quantify the bias in a two-way fixed effects approach, Figure A4 provides decomposition figures for our key outcomes (Goodman-Bacon, 2021). The figure shows that there is substantial heterogeneity across the different comparisons that two-way fixed effects uses in estimation of the average treatment effect on the treated (ATT), our target parameter. However, not all of these comparisons are "reasonable." In particular, the comparisons in which earlier treated units are used as a comparison group for later treated units are concerning (denoted as "Timing" groups in the figures). These comparisons reflect 43% of all comparisons used in a two-way fixed effects estimation of the ATT. Further, two-way fixed effects "variance weight" the data for efficiency, that is the estimator places the most weight on units that "turn on" treatment in the middle of the panel – i.e., 2013 in our study period. However, CBSAs adopting in this year are a relatively small cohort (n=20 or 7.6% of treated units), the most common years of adoption (i.e., cohorts) are 2014 (n=109 or 41.6% of treated units), 2015 (n=53 or 20.2% of treated units), and 2017 (n=51 or 19.5% of treated units). As discussed by Callaway and Sant'Anna (2021) weighting by group size is arguably a more appealing approach than variance weighting. These findings motivate our use of an

estimator that (unlike two-way fixed effects) prohibits such "forbidden" comparisons and does not weight estimates based on when (during the study period) a unit receives treatment for the first time. We emphasize results based on a procedure developed by Gardner (2022), but Table A3 shows that our results are robust to utilizing alternative estimators that are not vulnerable to such bias.

Figure A4: Goodman-Bacon (2021) Decomposition

Overall Difference−in−differences Estimate = .01281173
Within component = 1.7470281 (weight = 8.844e−06)

(a) Intensive Outpatient

Overall Difference−in−differences Estimate = −.0290307
Within component = −1.9475442 (weight = 8.844e−06)

(b) Non-intensive Outpatient

Notes: Sub-figures show the Goodman-Bacon decomposition for the noted outcomes. The estimation sample includes only Core Based Statistical Areas where UberX enters by 2019. Data are the Treatment Episode Data Set 2008 to 2018. The "Within" groups refer to earlier treated Core Based Statistical Areas being compared to not yet treated areas. The "Never Treated vs Timing" refers to Core Based Statistical Areas relative to the never treated areas (i.e., as in the main text, we define these as areas that get UberX entry in 2019). The "Timing" groups refer to comparisons between later treated versus earlier treated units. Comparisons in which earlier treated units are used as a comparison group for later treated units are concerning (Borusyak et al., 2024), these comparisons reflect 43% of all comparisons used in a two-way fixed effects estimation of the average treatment effect.

A11

Table A3: Effect of UberX Entry on Admissions per 1,000 (by Setting) to Substance Use Disorder Treatment using Alternate Estimators

| | Gardner (2022) | | Two-way Fixed Effects | |
	Intensive Outpatient	Non-intensive Outpatient	Intensive Outpatient	Non-intensive Outpatient
UberX entry	0.68***	-0.54**	0.01	-0.01
	(0.21)	(0.23)	(0.01)	(0.08)
Pre-treatment Mean	0.61	2.2	0.61	2.2
Core Based Statistical Areas	265	265	265	265
Treated Core Based Statistical Areas	260	260	260	260
Time Periods	11	11	11	11
Observations	2801	2801	2801	2801

| | de Chaisemartin and d'Haultfoeuille (2020) | | Callaway and Sant'Anna (2021) | |
	Intensive Outpatient	Non-intensive Outpatient	Intensive Outpatient	Non-intensive Outpatient
UberX Entry	0.25***	-0.55**	0.83***	-1.21**
	(0.12)	(0.20)	(0.28)	(0.41)
Pre-treatment Mean	0.63	2.25	0.61	2.2
Core Based Statistical Areas	218	218	265	265
Treated Core Based Statistical Areas	215	215	260	260
Time Periods	11	11	11	11
Observations	2398	2398	2801	2801

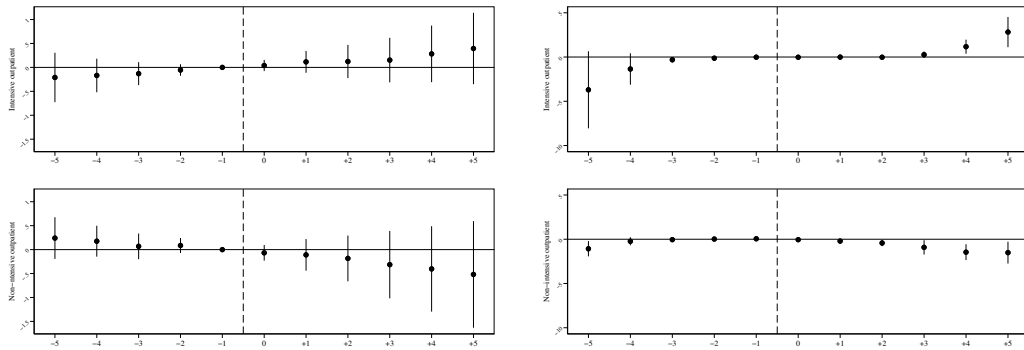| | Borusyak et al. (2024) | | Stacked - Cengiz et al. (2019) | |
	Intensive Outpatient	Non-intensive Outpatient	Intensive Outpatient	Non-intensive Outpatient
UberX	0.69***	-0.53**	0.78***	-0.62**
	(0.21)	(0.23)	(0.23)	(0.26)
Pre-treatment Mean	0.61	2.2	0.64	2.39
Core Based Statistical Areas	265	265	265	265
Treated Core Based Statistical Areas	260	260	210	210
Time Periods	11	11	11	11
Observations	2799	2799	3422	3422

Notes: The estimator is noted in the panel title. The estimation sample includes only Core Based Statistical Areas where UberX enters by 2019. Data are the Treatment Episode Data Set 2008 to 2018. All specifications control for Core Based Statistical Areas' number of substance use disorder treatment centers per 1,000 residents, Core Based Statistical Area fixed effects, and year fixed effects. The unit of observation is a Core Based Statistical Area in a year. Data are weighted by the Core Based Statistical Area population. Standard errors are clustered at the Core Based Statistical Area level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

A.5 Additional Event-studies and Parallel Trends Analyses

In this subsection, Figure A5 provides companion event-study analyses for our key outcomes of interest (intensive and non-intensive outpatient admissions) using the five alternate estimators introduced in subsection A.4. In Figure A6, we provide event-studies using the Gardner estimator by treatment cohort: 2012/2013, 2014, and 2015/2016. We see similar patterns across cohorts, but with larger effects for later treated cohorts. Importantly, we see evidence to support our parallel trends assumption across cohorts. Figure A7 provides the Gardner (2022) difference-in-differences estimates by treated cohort. These coefficient estimates show that UberX entry timing has similar effects on our outcomes of interest across entry cohorts in terms of sign, but the magnitude of effect size is somewhat larger for later versus earlier treated cohorts.

Finally, Figure A8 provides summary statistics for each of our outcomes by treatment cohort (2012/2013, 2014, and 2015/2016) from 2008 through 2012. The figures show that UberX did not systematically enter areas with increasing or decreasing admission trends at different times, again supporting the parallel trends assumption that allows us to consider difference-in-differences estimates as causal.

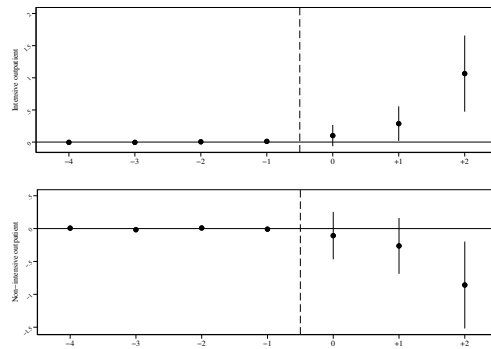# Figure A5: Event-studies using Alternate Estimators

(a) Two-Way Fixed Effects

(b) de Chaisemartin and D'Haultfoueille (2020)
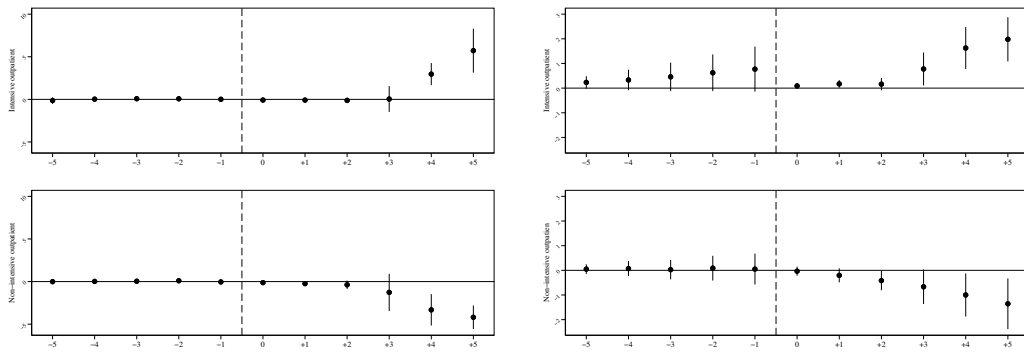
(c) Callaway and Sant'Anna (2021)

(d) Borusyak et al. (2024)

(e) Stacked - Cengiz et al. (2019)

Notes: Sub-figures show event-studies for each of our main outcomes using the noted estimator. These can be compared to sub-figures (d) and (e) in Figure 1. For the "stacked" estimates, we use only two post-treatment years to allow us to include 2016 UberX entries. We report the effect of UberX entry on intensive versus non-intensive outpatient changes per 1,000 population by entry cohort as noted. The estimation sample includes only Core Based Statistical Areas where UberX enters by 2019. Data are the Treatment Episode Data Set 2008 to 2018. All specifications control for Core Based Statistical Areas' number of substance use disorder treatment centers per 1,000 residents, Core Based Statistical Area fixed effects, and year fixed effects. The unit of observation is a Core Based Statistical Area in a year. Data are weighted by the Core Based Statistical Area population. 95% confidence intervals that account for within-Core Based Statistical Area clustering are reported with vertical lines.
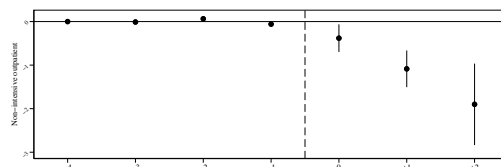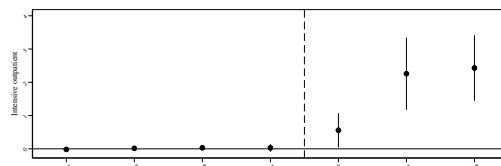
Figure A6: Event-studies for Specific Cohorts
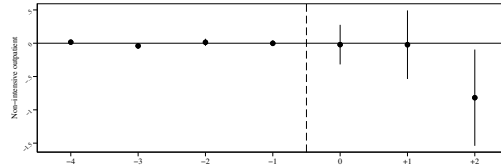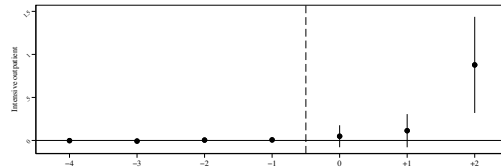
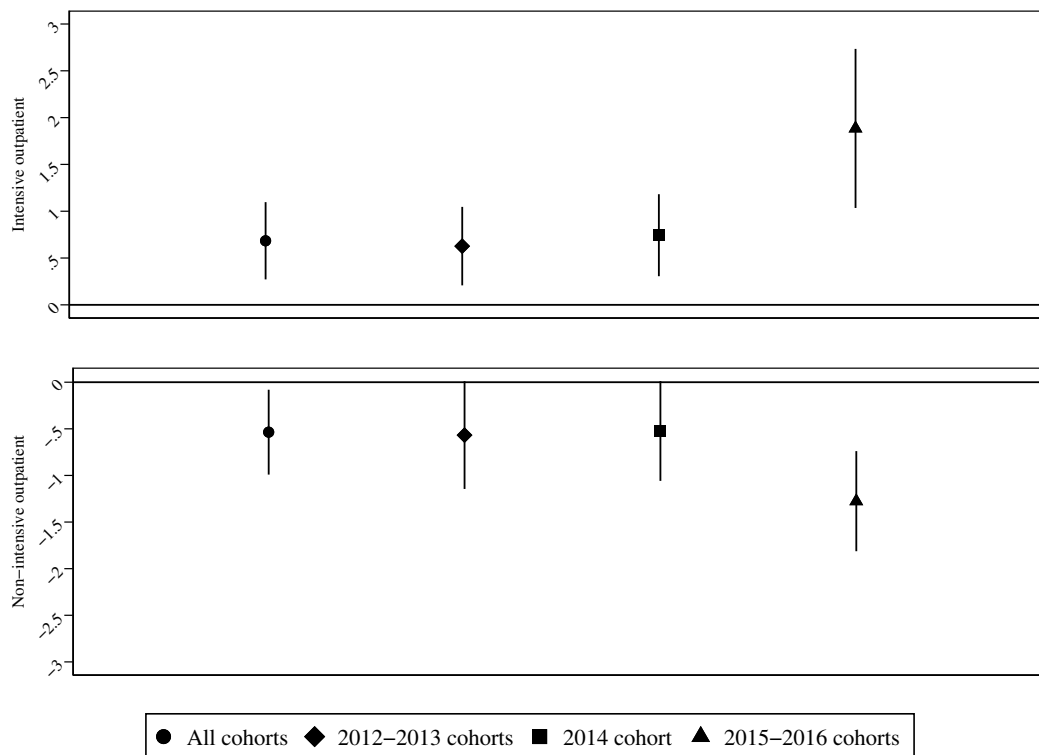(a) 2012/2013 Entry Cohort
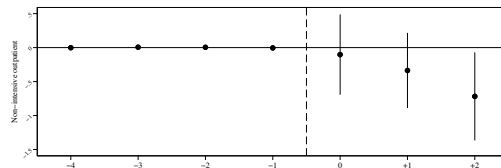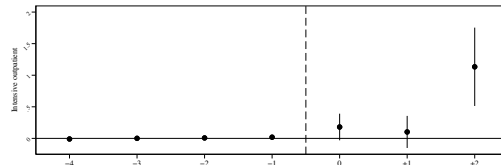
(b) 2014 Entry Cohort

(c) 2015/2016 Entry Cohort

Notes: Sub-figures show event-studies by cohort, as indicated, using the Gardner (2022) estimator. We show two years of post treatment data for all cohorts as our 2016 entries only have two years of post-treatment data (2017 and 2018). We report the effect of UberX entry on intensive versus non-intensive outpatient changes per 1,000 population by entry cohort as noted. The estimation sample includes only Core Based Statistical Areas where UberX enters by 2019. Data are the Treatment Episode Data Set 2008 to 2018. All regressions estimated with the Gardner (2022) two-step difference-in-differences procedure and control for Core Based Statistical Areas' number of substance use disorder treatment centers per 1,000 residents, Core Based Statistical Area fixed effects, and year fixed effects. The unit of observation is a Core Based Statistical Area in a year. Data are weighted by the Core Based Statistical Area population. 95% confidence intervals that account for within-Core Based Statistical Area clustering are reported with vertical lines.

Figure A7: Difference-in-Difference Effect Size by Entry Cohort

Notes: We report the effect of UberX entry on intensive versus non-intensive outpatient changes per 1,000 population by entry cohort as noted. The estimation sample includes only Core Based Statistical Areas where UberX enters by 2019. Data are the Treatment Episode Data Set 2008 to 2018. All regressions estimated with the Gardner (2022) two-step difference-in-differences procedure and control for Core Based Statistical Areas' number of substance use disorder treatment centers per 1,000 residents, Core Based Statistical Area fixed effects, and year fixed effects. The unit of observation is a Core Based Statistical Area in a year. Data are weighted by the Core Based Statistical Area population. 95% confidence intervals that account for within-Core Based Statistical Area clustering are reported with vertical lines.
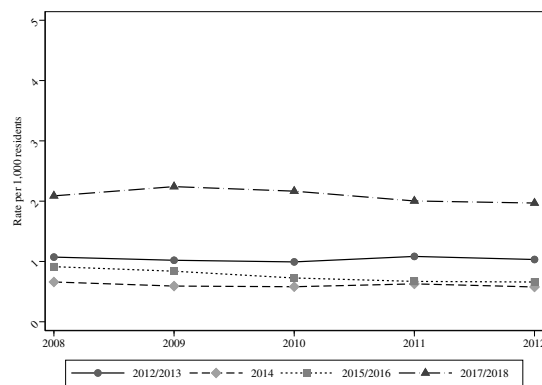
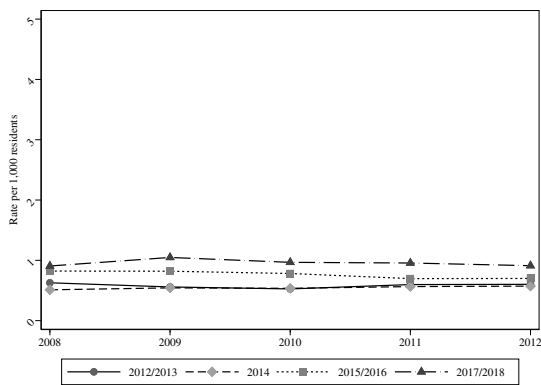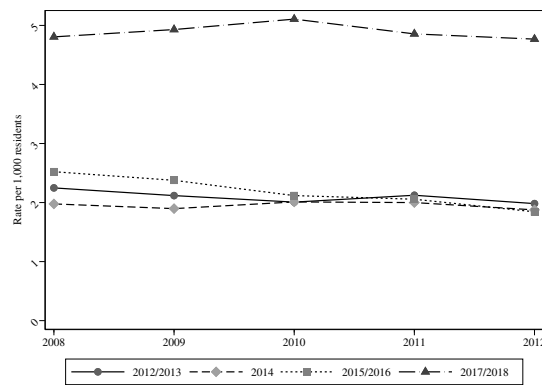## Figure A8: Cohort Trends
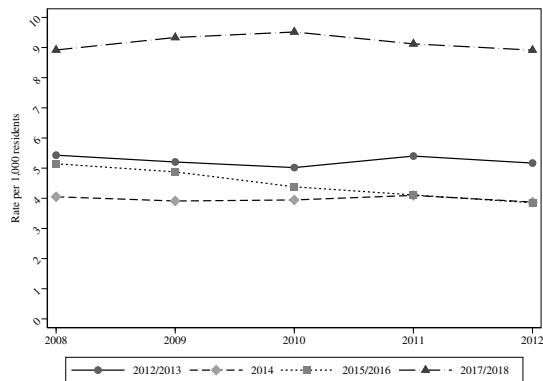
(a) Total
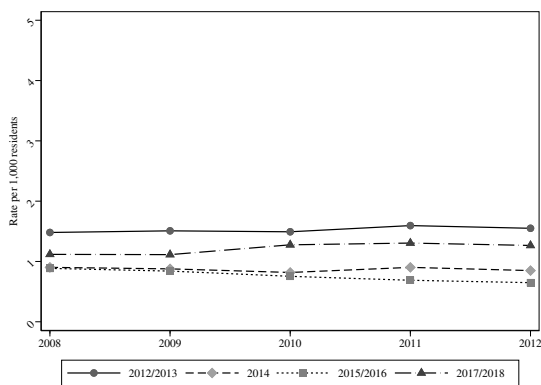
(b) Detoxification

(c) Residential

(d) Intensive

(e) Non-Intensive

Notes: Sub-figures show trends in admissions for each of our main outcomes in the years before UberX entry.

A.6 Does UberX Affect Provider Capacity or Increase Substance Use Directly?

In Table A4, we report the effect of UberX entry on the share of patients who wait more than two weeks and more than 30 days for admission to outpatient treatment. There, we see no statistically significant changes in the proportion of patients waiting more than either two weeks or more than 30 days. The purpose of this analysis is to show that UberX entry has little to no effect on provider capacity. If UberX changes demand for substance use treatment on the extensive margin (e.g., reductions in DUI-related referrals), we would expect to see reduced waiting times. Instead, we find statistically insignificant positive effects only on wait times for intensive outpatient treatment, a pattern consistent with expanded transportation availability leading patients to opt for intensive rather than non-intensive outpatient services.

In Table A5, we present coefficient estimates for changes in the proportion of admissions to intensive and non-intensive outpatient treatment with daily substance use. We present similar coefficient 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 estimates 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.

Table A4: Effect of UberX Entry on Waiting Time for Entry to Substance Use Disorder Treatment: Treatment Episode Data Set 2008-2018

	Share that Wait More than Two Weeks		Share that Wait More than 30 Days	
	Intensive outpatient	Non-intensive outpatient	Intensive outpatient	Non-intensive outpatient
UberX Entry	0.037	-0.002	0.043	0.005
	(0.034)	(0.024)	(0.026)	(0.021)
Pre-treatment mean	0.08	0.09	0.03	0.04
Core Based Statistical Areas	199	199	199	199
Treated Core Based Statistical Areas	185	185	185	185
Time periods	11	11	11	11
Observations	1603	1838	1603	1838

Notes: The estimation sample includes only Core Based Statistical Areas where UberX enters by 2019. Data are the Treatment Episode Data Set 2008 to 2018. Information on days waiting for treatment is not included in the mandatory component of the Treatment Episode Data Set and thus the sample size is smaller than our main estimation sample. All regressions estimated with the Gardner (2022) two-step difference-in-differences procedure and control for Core Based Statistical Areas' number of substance use disorder treatment centers per 1,000 residents, Core Based Statistical Area fixed effects, and year fixed effects. The unit of observation is a Core Based Statistical Area in a year. Data are weighted by the Core Based Statistical Area population. Standard errors are clustered at the Core Based Statistical Area level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	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
Core Based Statistical Areas	265	265	242	248	250	250
Treated Core Based Statistical Areas	260	260	240	246	228	228
Time periods	11	11	11	11	11	11
Observations	2379	2738	2060	2235	2060	2235

Notes: The estimation sample includes only Core Based Statistical Areas where UberX enters by 2019. Data are the Treatment Episode Data Set Discharges 2008 to 2018. All regressions estimated with the Gardner (2022) two-step difference-in-differences procedure and control for Core Based Statistical Areas' number of substance use disorder treatment centers per 1,000 residents, Core Based Statistical Area fixed effects, and year fixed effects. The unit of observation is a Core Based Statistical Area in a year. Data are weighted by the Core Based Statistical Area population. Standard errors are clustered at the Core Based Statistical Area 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 UberX 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 Core Based Statistical Area
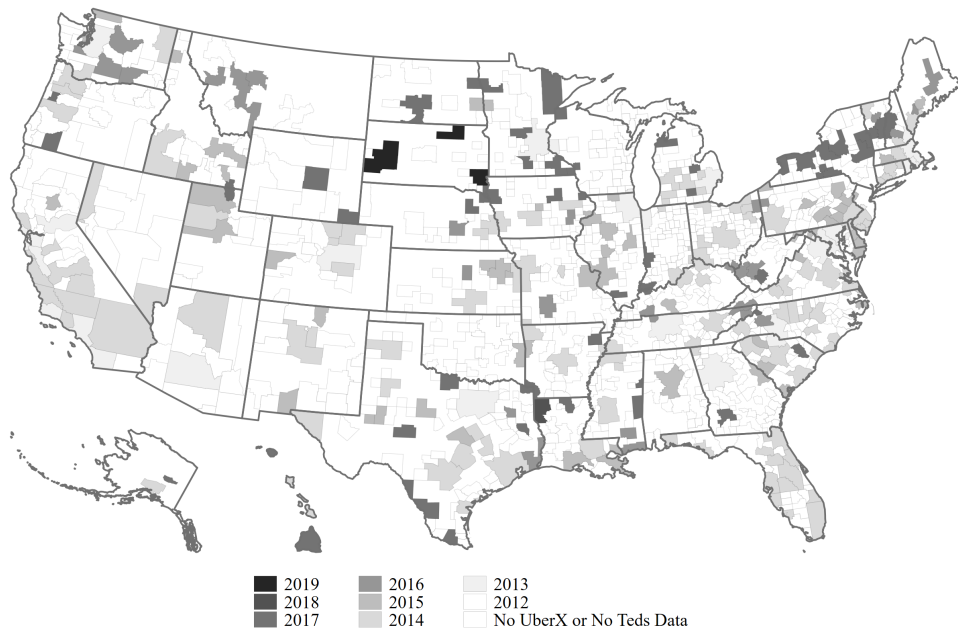
■ 2019	■ 2016	▫ 2013	
■ 2018	▫ 2015	▫ 2012	
■ 2017	▫ 2014	▫ No UberX or No Teds Data	

Note: This map shows all Core Based Statistical Areas in gray outline. Areas with no known UberX entry date or without Treatment Episode Data Set data are white. Areas that ever experience a known UberX entry by the end of 2019 are shaded gray according to their year of entry. Darker colors indicate earlier UberX entry. Note that Core Based Statistical Areas with 2019 UberX entry serve only as control areas in our analyses.

Figure B2: Entry of UberX By Core Based Statistical Area Over Time
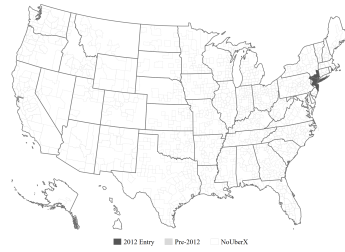
(a) 2012 UberX Entry

(b) 2013 UberX Entry

(c) 2014 UberX Entry

(d) 2015 UberX Entry
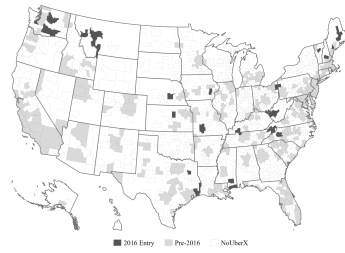
(e) 2016 UberX Entry
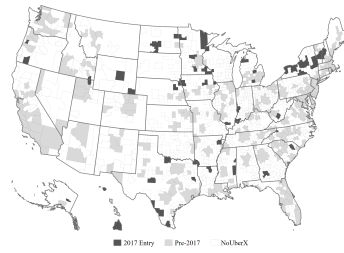
(f) 2017 UberX Entry
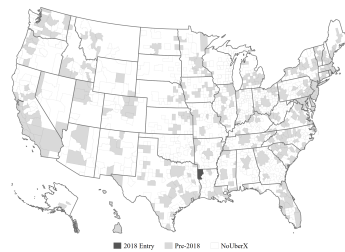
(g) 2018 UberX Entry
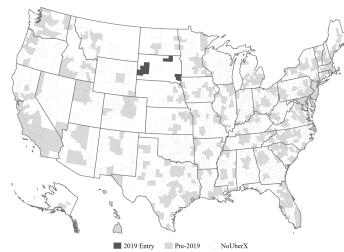
(h) 2019 UberX Entry

Note: This map shows all Core Based Statistical Areas in gray outline. Areas with no known UberX entry date or without Treatment Episode Data Set data are white. Areas that ever experience a known UberX entry by the end of 2019 are shaded gray according to their year of entry. Darker colors indicate earlier UberX entry. Note that Core Based Statistical Areas with 2019 UberX entry serve only as control areas in our analyses.

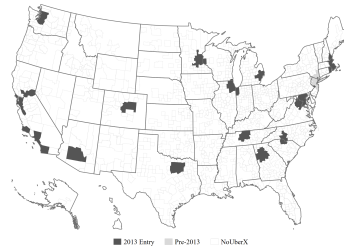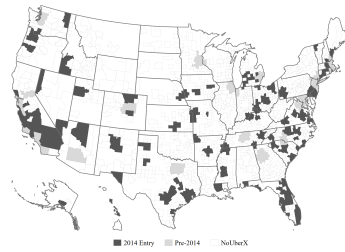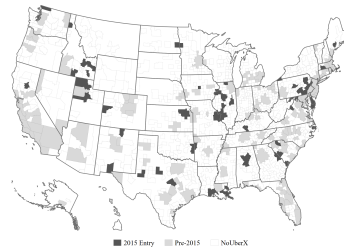| Core Based Statistical Area/Division Code (1)	Core Based Statistical Area/Division Title (2)	Date UberX Entered (3)	Core Based Statistical Area/Division Code (1)	Core Based Statistical Area/Division Title (2)	Date UberX Entered (3)
20524*	Dutchess County-Putnam County, NY	08/24/2012	40900	Sacramento–Roseville–Arden-Arcade, 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 Division level, these cases are denoted by a star in column (1). Otherwise Core Based Statistical Area codes and titles refer to Core Based Statistical Areas.

Core Based Statistical Area/Division Code	Core Based Statistical Area/Division Title	Date UberX Entered	Core Based Statistical Area/Division Code	Core Based Statistical Area/Division Title	Date UberX Entered
(1)	(2)	(3)	(1)	(2)	(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 Division level, these cases are denoted by a star in column (1). Otherwise Core Based Statistical Area codes and titles refer to Core Based Statistical Areas.

Core Based Statistical Area/Division Code (1)	Core Based Statistical Area/Division Title (2)	Date UberX Entered (3)	Core Based Statistical Area/Division Code (1)	Core Based Statistical 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 Division level, these cases are denoted by a star in column (1). Otherwise Core Cased Statistical Area codes and titles refer to Core Based Statistical Areas.

Core Based Statistical Area/Division Code	Core Based Statistical Area/Division Title	Date UberX Entered	Core Based Statistical Area/Division Code	Core Based Statistical Area/Division Title	Date UberX Entered
(1)	(2)	(3)	(1)	(2)	(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 Division level, these cases are denoted by a star in column (1). Otherwise Core Based Statistical Area codes and titles refer to Core Based Statistical Areas.

Table B5: Complete UberX Entry Dates 5 of 7

Core Based Statistical Area/Division Code (1)	Core Based Statistical Area/Division Title (2)	Date UberX Entered (3)	Core Based Statistical Area/Division Code (1)	Core Based Statistical Area/Division Title (2)	Date UberX Entered (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

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Core Based Statistical Area/Division Code	Core Based Statistical Area/Division Title	Date UberX Entered	Core Based Statistical Area/Division Code	Core Based Statistical 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

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Core Based Statistical Area/Division Code (1)	Core Based Statistical Area/Division Title (2)	Date UberX Entered (3)	Core Based Statistical Area/Division Code (1)	Core Based Statistical Area/Division Title (2)	Date UberX Entered (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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