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Ridesharing and substance use disorder treatment[☆]

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A B S T R A C T

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.

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

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

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– 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 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 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.

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 1000 residents (24.4%) following UberX entry in a CBSA. This decline is fully offset by an increase of 0.68 intensive outpatient admissions per 1000 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 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 our findings are related to a significant change in transportation access among people seeking substance use disorder treatment. We show that our estimates are robust to a variety of alternate specifications and sample restrictions. Moreover, we present event-studies that support the parallel trends assumption, and show that the treatment effects increase over time following UberX entry, 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).

Our work connects to at least two strands of economic literature. First, we make several contributions to the existing literature on the impact of ridesharing. For example, Moskatel and Slusky (2019) show that ridesharing services are used as an alternative to ambulances. Our findings provide further evidence that ridesharing can reduce transportation barriers and improve access to healthcare. Our work also shows that UberX can help individuals receive their preferred treatment for substance use disorders,

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[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.

[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/; last accessed 9/7/2024).

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

[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.

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

which is of critical importance given that ridesharing has also been shown to increase alcohol consumption (Zhou, 2020; Teltser et al., 2021). More broadly, our work adds to society's understanding of the transformative effects of ridesharing on communities, where the existing literature has also uncovered significant impacts on labor markets (Berger et al., 2018; Chen et al., 2019), public transit usage and congestion (Hall et al., 2018; Tarduno, 2021; Agrawal and Zhao, 2023), air quality (Kim and Sarmiento, 2021; Krishnamurthy and Ngo, 2024), crime (Dills and Mulholland, 2018), and traffic fatalities and drunk driving (Brazil and Kirk, 2016; Greenwood and Wattal, 2017; Anderson and Davis, In press; Barrios et al., 2023).

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; 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.

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 education and vocational programming, social skills development, financial planning, legal advocacy, and assistance with access to social services.

[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.

[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.

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 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]

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 1000 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 h 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 h 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 1000 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 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.

[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.

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

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 data would likely attenuate our estimates of interest.

3.2. Estimation

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

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

In Eq. (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 time-varying per-capita number of substance use disorder treatment centers in the CBSA (U.S. Census Bureau, 2022), 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_{jt} 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 Eq. (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 Eq. (1) and Eq. (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 Eqs. (1) and (2) creates the potential for heterogeneous and dynamic treatment effect bias (Baker et al., 2022). This type of bias occurs in settings with staggered treatment adoption when the treatment effect is not constant over time. For example, UberX use tends to increase over time (Bagchi, 2018; Hall and Krueger, 2018). Eq. (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 show that the Borusyak et al. (2024), Callaway and Sant'Anna (2021), and other estimators produce nearly identical estimates.

[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.

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

[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.

Table 1
Effect of UberX Entry on Admissions per 1000 (by Setting) to Substance Use Disorder Treatment using Gardner Two-Stage Difference-in-Differences: Treatment Episode Data Set 2008–2018.

	Total (1)	Detoxification (2)	Residential (3)	Intensive Outpatient (4)	Non-intensive Outpatient (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.

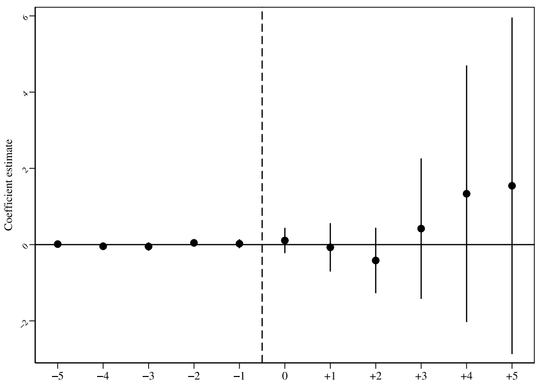
4. Findings

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 1000 population per year (28%). The decline in non-intensive outpatient admissions is fully offset by an increase of 0.69 per 1000 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 capture the movement from different treatment settings (such as a transition from non-intensive outpatient to intensive outpatient) as two separate treatment admissions (Substance Abuse and Mental Health Services Administration, 2022). Thus, the offsetting effects on intensive and non-intensive outpatient admissions suggest that substitution occurs among new arrivals rather than mid-treatment switchers.

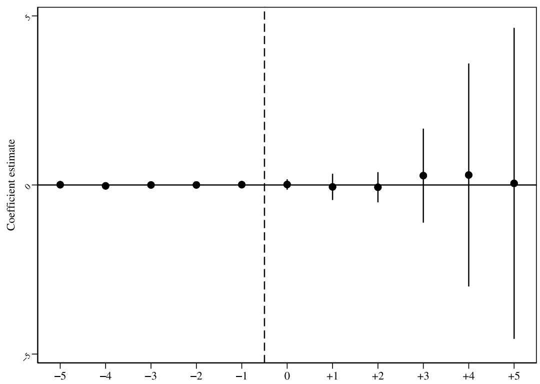
In Panel B of Table 1, where we include the per-capita number of treatment centers as an additional time-varying CBSA-level covariate to address the concern that UberX entry may be correlated with the emergence of new treatment centers, we find very similar coefficient estimates. Specifically, we find a decrease of 0.54 non-intensive outpatient admissions with a corresponding increase of 0.68 intensive outpatient admissions. We have tested whether the absolute value of the non-intensive and intensive outpatient coefficient estimates are statistically different from each other using a non-parametric bootstrap (500 repetitions). The difference is not statistically significant at conventional levels (p-value = 0.577). Additionally, when we regress the number of centers per capita on UberX entry into a CBSA using Eq. (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 Fig. 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

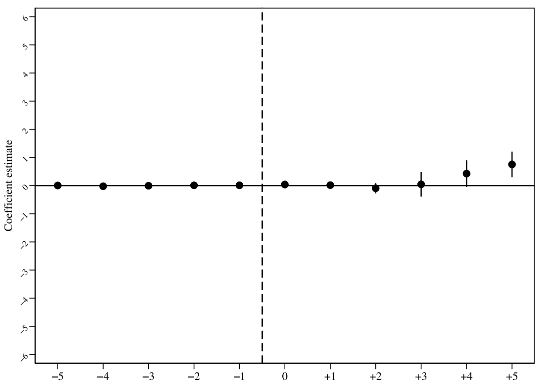
[19] Authors' calculation based on the 2018 National Survey on Substance Abuse Treatment Services Survey (N-SSATS). N-SSATS, administered by SAMHSA, is used by the federal government to track the provision of substance use disorder treatment in the U.S.



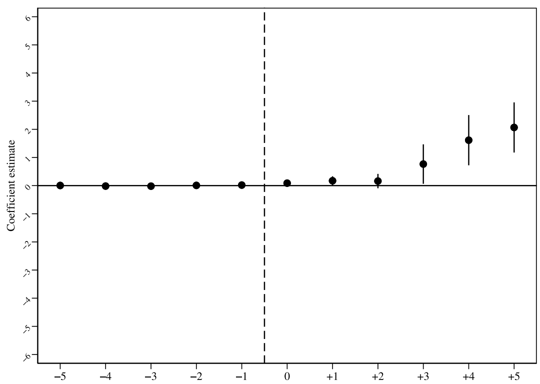
(a) Total Admissions



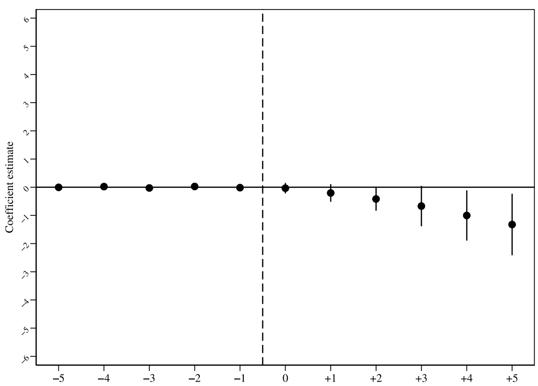
(b) Detoxification



(c) Residential



(d) Intensive Outpatient



(e) Non-intensive Outpatient

Fig. 1. Event-studies.
Notes: These event-study figures show the effect of UberX entry on the noted outcome per 1000 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 1000 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.

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

In Fig. 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 as evidence that supports a causal interpretation of our findings. We also observe larger effects among men and minority groups.

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

In Fig. 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 1000 population. While not included in Fig. 4, we also examine 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

[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.

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

[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).

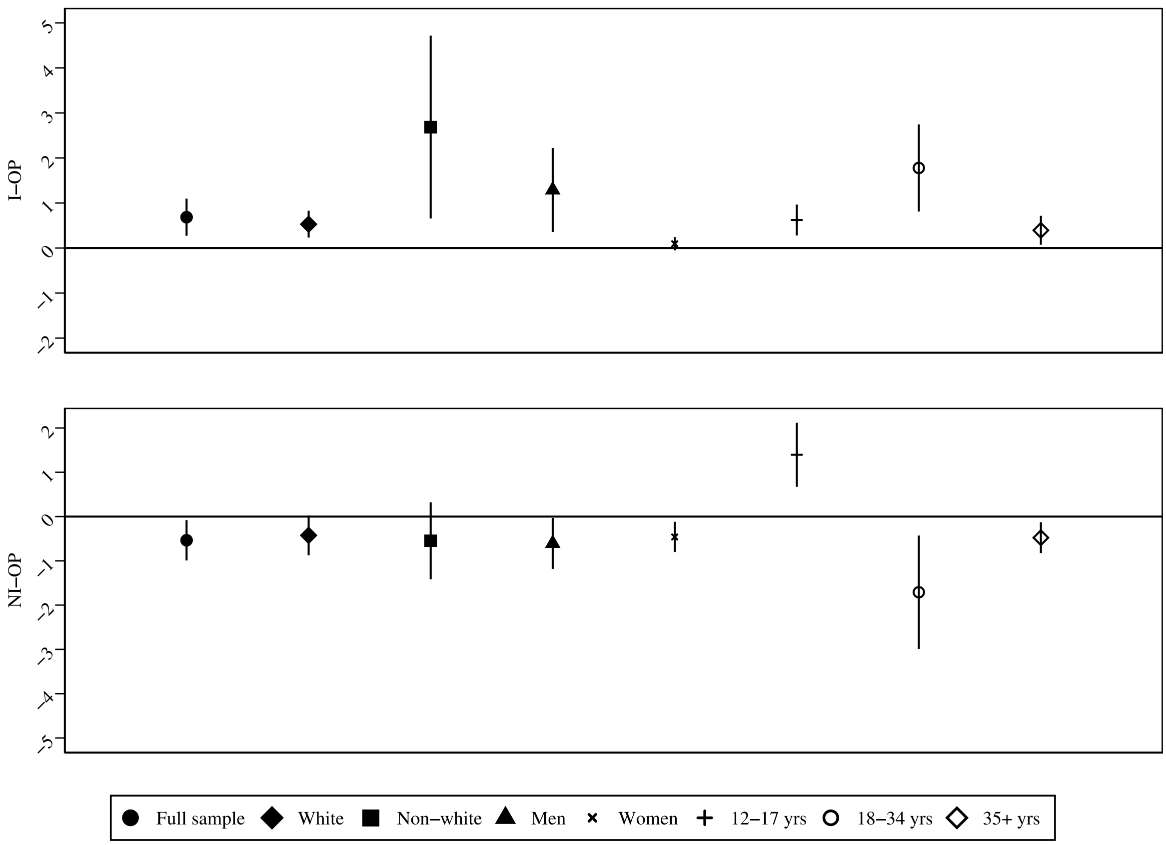


Fig. 2. Demographic Heterogeneity of Intensive versus Non-Intensive Outpatient Effects.
Notes: We report the effect of UberX entry on the intensive versus non-intensive outpatient changes per 1000 population for various demographic subgroups. The legend explains the relevant subgroup sample restriction 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 1000 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.

receive MOUD, but do so 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 towards 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 timing.

[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.

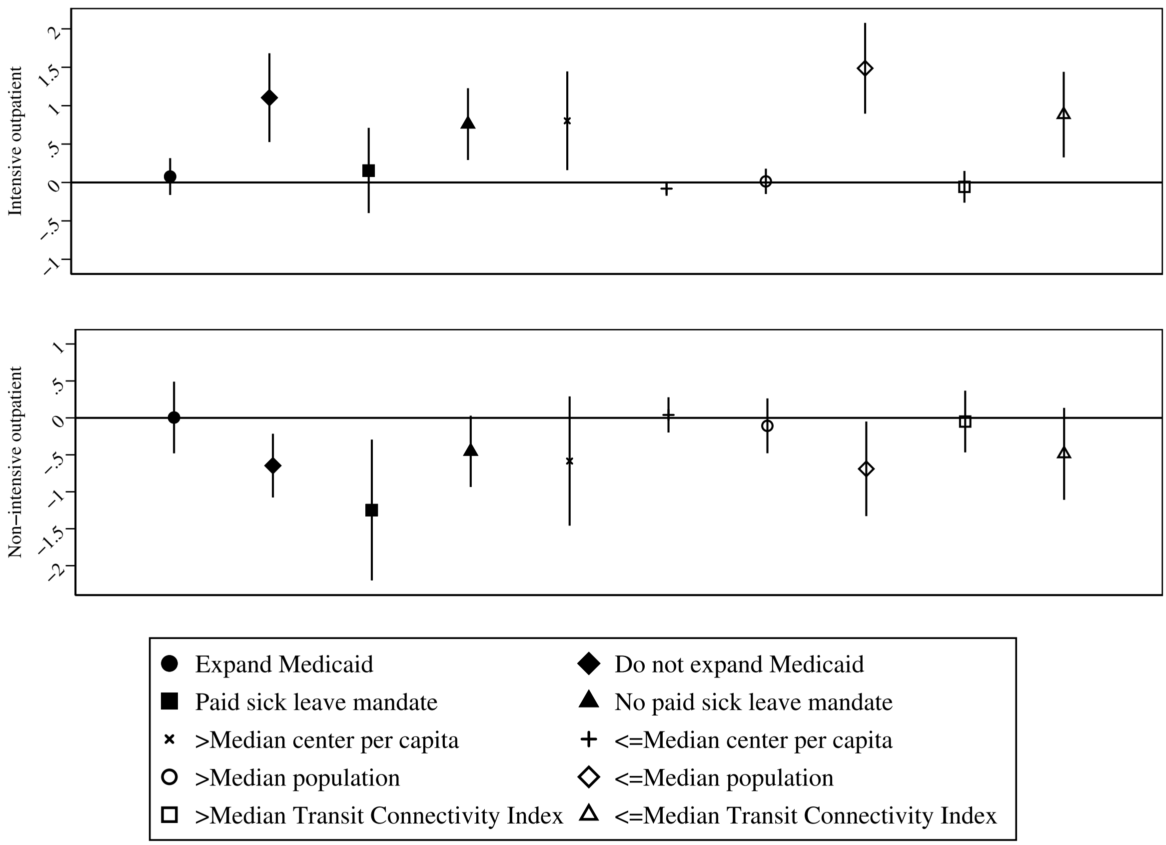


Fig. 3. Area-Level Heterogeneity of Intensive versus Non-Intensive Outpatient Effects.
Notes: We report the effect of UberX entry on the intensive versus non-intensive outpatient changes per 1000 population by area characteristics. The legend explains the relevant sample restriction that produces the 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 1000 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.

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]

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.

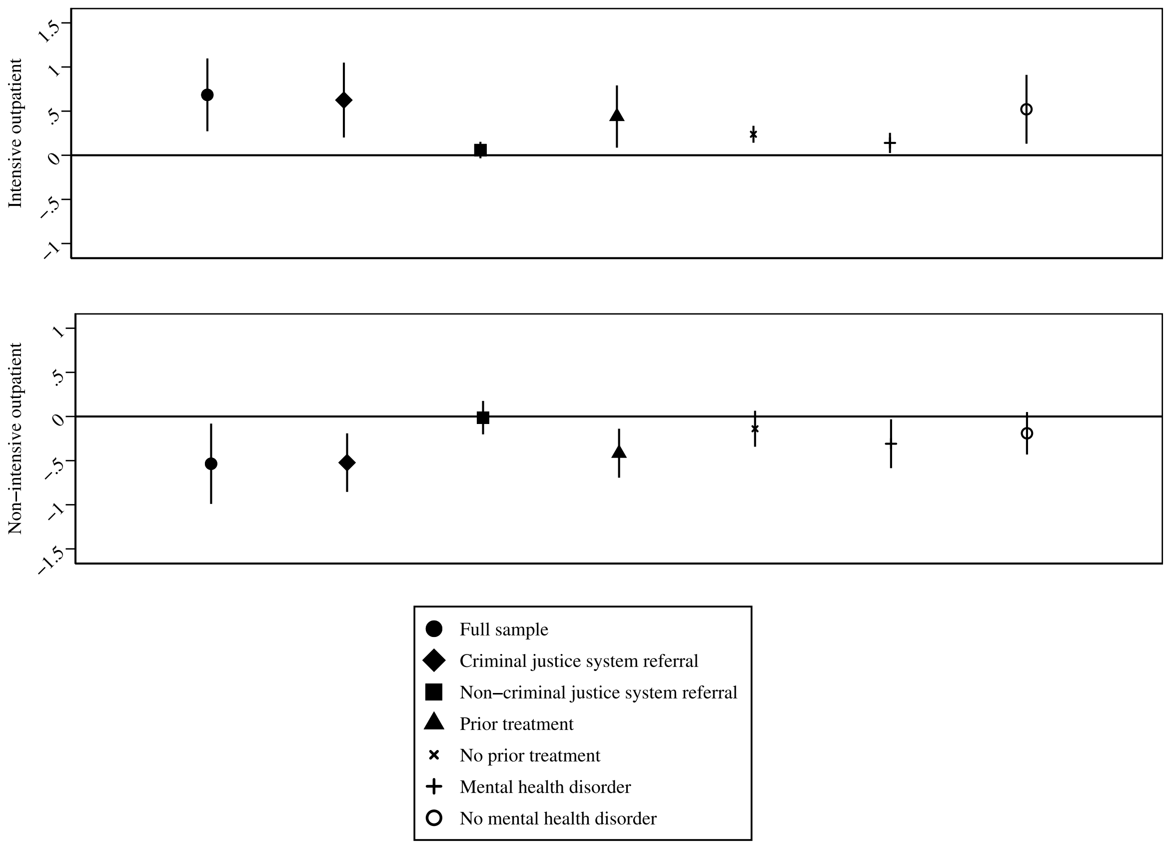


Fig. 4. Clinical Characteristic Heterogeneity of Intensive versus Non-Intensive Outpatient Effects.
Notes: We report the effect of UberX entry on the intensive versus non-intensive outpatient admissions per 1000 population by clinical characteristics. The legend explains the relevant sample restriction 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 1000 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.

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 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 effect on wait times for NI-OP treatment, and positive but statistically insignificant effects on wait times for I-OP treatment.

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.

[28] Detailed results are available upon request. We find an increase in DUI-related NI-OP of 0.04 per 1000 per year, which is statistically significant at the 10% level, and an increase in DUI-related I-OP of 0.15 per 1000 per year, which is statistically significant at the 1% level.

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 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.

CRediT authorship contribution statement

Conor Lennon: Writing – review & editing, Writing – original draft, Methodology, Investigation, Data curation, Conceptualization. **Johanna Catherine Maclean:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Keith Teltser:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

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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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jhealeco.2024.102941.

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