Driving Inclusion: The Effect of Improved Transportation for People with Disabilities*

Melissa Gentry‡

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Abstract

People with disabilities face substantial barriers to economic and social participation. I explore the extent to which these barriers are overcome by the availability of reliable and flexible transportation. Leveraging the roll-out of Uber, I use a stacked difference-in-differences approach to show that the availability of reliable and flexible transportation leads to improvements in social and economic participation through increased marriage rates and employment. As paratransit trips cost public agencies more per ride than comparable rideshare alternatives, these findings suggest that reallocating some existing federal transportation subsidies toward public-private partnerships may be a promising avenue for policy.

JEL Codes: J0, J14

*Throughout this paper I will use both person-first and identity-first language to describe the population of individuals with disabilities, as is recommended by the National Institutes of Health.

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1 Introduction

People with disabilities represent a significant and growing part of the population, comprising approximately 11% of the prime-age U.S. population. This large group fares substantially worse than their non-disabled peers on traditional measures of well-being, including lower employment rates (42% vs 81%), lower average earnings ($15,797 vs $40,767), higher rates of reliance on social assistance programs (23% vs 2%), and lower rates of marriage (36% vs 53%).[1] Barriers to economic and social inclusion have long been documented for this vulnerable population (Bellemare et al. 2023; Maestas, Mullen, and Rennane 2019; Schur, Kruse, and Blanck 2013). Finding ways to reduce barriers and improve labor force engagement for disabled adults would lead to overall improved individual well-being (Graham and Pinto 2020). Moreover, addressing barriers would not only benefit people with disabilities but would also lead to broader societal implications including increased tax revenues, reduced reliance on government support, and reduced need for care-giving support (Banks and Polack 2015; Saunders and Nedelec 2014).

People with disabilities often cite transportation as a major barrier to both economic and social inclusion (Bezyak, Sabella, Hammel, et al. 2020; Lindsay 2011; Rintala et al. 1997; Sabella and Bezyak 2019).[2] Indeed, people with disabilities have specifically cited transportation as a barrier to dating and romantic relationships (Rintala et al. 1997), suggesting that transportation difficulties may contribute to the lower marriage rates observed among this population. In a recent survey, more than 60% of respondents with disabilities reported sometimes, usually, or always having difficulties accessing transportation to get around their community (Bezyak, Sabella, Hammel, et al. 2020). Although access to public transportation is a guaranteed right under the Americans with Disabilities Act, existing transportation options, particularly traditional paratransit services, often fail to meet the needs of people with disabilities. These services are plagued by inflexible scheduling, unreliability, and limited availability, making it difficult for disabled individuals to maintain employment, access

[1] Source: Table 1, American Community Survey 2006-2019

[2] Transportation access is commonly cited as a barrier to work among individuals who are unemployed and out of the labor force, but existing evidence on the impact of transportation access is mixed. For a review of the literature, see Bastiaanssen, Johnson, and Lucas (2020).

essential services, or engage in social activities (Rogers et al. 2021; Sears 2023).[3] Local news sources commonly run stories about the shortcomings of paratransit services for customers (Beyer and Williams 2024; Kilmer 2024; Wiley 2023). A quote from one local news article articulates the existing limitations succinctly, "If it's not reliable, it's not accessible. And if it's not accessible, then what's the point?" (Rogers et al. 2021). While it is generally accepted that the lack of reliable and flexible transportation may be a barrier to social and economic inclusion, there is little empirical evidence that attempts to understand the role it plays or the extent to which the availability of better options would allow disabled individuals to overcome it.

In this paper, I explore the extent to which these barriers are overcome by the availability of reliable and flexible transportation. To do so, I take advantage of the availability of ridesharing platforms in one's area. These platforms, while unlikely to be a day to day mode of transportation, may act as a type of "reliability insurance" when typical transit methods fall short. I investigate how the availability of flexible and reliable transportation, provided via Uber, can alleviate existing accessibility challenges and enhance the quality-of-life for people with disabilities.

I contribute to the literature by providing the first evidence on the effects of flexible and reliable transportation access on key quality-of-life outcomes for people with disabilities. In addition to estimating effects on measures of labor market engagement, I consider the effect of Uber on marriage and household composition, which provides a more holistic sense of the effect of flexible transportation on quality of life for individuals with disabilities, especially considering the role that transportation access plays in social inclusion.

Employing a stacked difference-in-differences approach, with data from the American Community Survey (ACS), I explore Uber's impact on outcomes such as employment status, labor force participation, public assistance receipt, and marital status. I find that the introduction of flexible on-demand transportation in a city leads to statistically and economically significant improvements in outcomes for adults with disabilities. Employment for disabled

[3]Most paratransit programs require reservations at least one day in advance and while many programs have an on-time (within 30 minutes of reservation) pick-up rate of 90%, some only have on-time pick-ups 70% of the time. For people reliant on paratransit in places with only a 70% on-time rate, they can expect to be late at least once every five days.

adults increases by 1.2 percentage points (a 3% increase over the control mean), wages increase by $576 a year (a 4.8% increase), and marriage rates increase by 2.3 percentage points (6%). For context, the magnitude of the increase in marriage rates is 13% of the marriage gap between prime age disabled and non-disabled individuals. These findings indicate that alleviating transportation barriers can improve the economic and social participation of this vulnerable population.

To better understand these main effects, I explore how the effects of improved transportation access vary by an individual's demographics, type of disability, and baseline differences in alternative transportation options. Since the functional limitations associated with different disabilities may make it easier or harder to engage with the labor market, one might expect improving transportation to have varying effectiveness for different groups. Indeed, the main effects are heterogeneous across subgroups. The key takeaway from this heterogeneity analyses is that the groups with higher rate of baseline labor force engagement are those who appear to be affected most. This indicates that improving transportation alone may not be sufficient to significantly improve employment for people of all disability types. Further, I find that effects are mixed based on the quality of local public transportation – employment effects are concentrated among places with higher quality transit, whereas marriage effects are strongest in places with lower quality public transit.

In the United States, accessible public transportation is already often subsidized by federal grants, yet traditional paratransit services remain costly and frequently fail to meet the needs of people with disabilities. Paratransit trips are expensive to operate, often costing public agencies far more per ride than a comparable rideshare trip, implying that even though rideshare services can be prohibitively expensive for individual users, they may actually represent a cost savings from the perspective of a public transit agency. Federal paratransit funding already represents a substantial public commitment, and evidence that on-demand rideshare services can meaningfully improve employment and social participation for this population suggests there may be cost efficiencies available through reallocation. Encouraging public-private partnerships, or the development of on-demand local transit services, through these existing federal government programs may therefore be a promising avenue for future transportation policy.

2 Background

2.1 People with Disabilities

According to World Health Organization (2023), 1 in 6 people in the world have a disability, making it the world's largest marginalized group. In the 2019 5-Year American Community Survey, the share of the total US population with disabilities was 13.2% (approximately 42 million individuals) and the prime-age share was 10.5%. This group has historically faced many barriers to employment and social inclusion (Maestas, Mullen, and Rennane 2019; Schur, Kruse, and Blanck 2013). Prior to the 1970s, "the exclusion and segregation of people with disabilities was not viewed as discrimination" (Mayerson 1992). Even now, after legislation that forbade discrimination towards people with disabilities, researchers continue to observe evidence of employment discrimination for this population (Ameri et al. 2018; Bellemare et al. 2023).

Barriers to labor market inclusion for people with disabilities can arise from both demand-side and supply-side factors. Employers may have concerns that workers with disabilities would have lower productivity than non-disabled workers (Jones 2006) or that accommodations mandated by the Americans with Disabilities Act may be costly (Acemoglu and Angrist 2001). People with disabilities also face other barriers to employment such as health limitations (Currie and Madrian 1999), or lack of training (Baldwin and Johnson 1994, 2000; Lindsay 2011). I will be the first to consider the understudied role of flexible, on-demand transportation access as a supply-side factor for economic inclusion among people with disabilities.

Another factor that may contribute to social or labor market exclusion is related to the disincentives that accompany Social Security Disability Insurance (SSDI) and Supplemental Security Income (SSI). While there is evidence that disability insurance reduces financial risk for recipients (Deshpande, Gross, and Su 2021) there is also evidence that labor force participation would be higher among recipients in the absence of disability insurance receipt (French and Song 2014; Maestas, Mullen, and Strand 2013). Recipients of SSI also claim that the strict asset limits associated with eligibility make it so that many recipients are unable to marry or live with an unmarried partner without losing their benefits (Garbero

2020; Pulrang 2022). I contribute to the existing literature on disability benefit programs by investigating a setting in which there could be consequences for benefit take-up and subsequently marriage decisions for prime age disabled adults.

One of the challenges of disability research is that as society's perceptions of disability changes, so do survey questions about disability. Moreover, different surveys use varying definitions of disability. I use data from the American Community Survey (ACS) which has a series of questions to elicit information on disability status. The ACS asks questions about five broad types of disability: self care, independent living, ambulation, cognition, and vision/hearing.[4] Each of these categories refer specifically to non-temporary difficulties which means, for example, a broken leg would not count as an ambulatory disability. Each category is not mutually exclusive; people can respond positively to more than one question. Throughout this analysis, when I refer to disabled individuals I refer to anyone who answered positively to any of the disability questions.

With this definition in mind, the summary statistics for my sample (Table 1) demonstrate that disabled individuals experience lower socioeconomic outcomes compared their non-disabled peers. People with disabilities in my sample have lower employment rates (42% vs. 81%), labor force participation rates (50% vs. 86%), and incomes ($22,565 vs. $44,721), as well as higher rates of public assistance receipt (23% vs. 2%) compared to those without disabilities. While it is true that not every disabled person is willing or even able to work, this population still faces unemployment rates that are double those of the non-disabled population.[5] People with disabilities are also older, less likely to be married, and have lower levels of educational attainment. Addressing existing transportation limitations has the potential to mitigate some of these disparities.

[4]In later years, the vision and hearing questions were separated. For consistency across years, I will use the binned version. Specific questions from the ACS can be found in Appendix A. Earlier survey data was limited to a definition of disability that focused on "work-related disability" or health conditions that impacted the type or amount of work an individual was able to do. I am not using work disability in this paper.

[5]According to BLS 2024 the 2019 unemployment rate for people with disabilities was 7.3% while the non-disabled rate was 3.5.

2.2 Transportation for People with Disabilities

Transportation stands out as a major barrier to economic inclusion for disabled people. Of 12 papers that ask people with disabilities about the barriers to employment they face, 9 specifically mention transportation as an important barrier.[6] To better understand the current state of transportation use, Appendix Table D1 presents the typical modes of travel to work by disability status using data from the Current Population Survey Disability Supplement in 2012. These data are restricted to only individuals who are employed but they illustrate that employed people with disabilities are less likely to use private vehicles (73% vs. 85%) and are more likely to rely on public transportation or paratransit services. These public transportation and paratransit services may have physical barriers (such as non-accessible buses and trains), sensory barriers (such as a lack of audible signals for the visually impaired), or systemic barriers (like inflexible scheduling requirements) which can make them inadequate for many users (Bezyak, Sabella, and Gattis 2017 and Sabella and Bezyak 2019).

News articles paint a picture of unreliability - by law, paratransit drivers must arrive within 30 minutes of a scheduled pick up time to be considered "on time" but the reality often falls short of this benchmark. In one incident in Maryland, investigators found that a rider scheduled for an 8:30 p.m. pick-up was notified after her scheduled time that she would not be picked up until 2:37 a.m. (Sears 2023). While many paratransit programs across the United States have an on-time-performance percentage of 90% or greater, some fall short of what is deemed the standard for satisfactory service. In these regions, the share of rides that are within a set pick up window (usually thirty minutes to an hour) and thus considered "on-time" can be as low as 70% (Christman 2024; Intercity Transit 2021; Martinez 2021; RTC of Southern Nevada 2024; San Francisco Municipal Transportation Agency 2024; Sears 2023). An attorney for a disability advocacy nonprofit in Chicago told journalists, "Many of the people we work with had jobs and lost them simply because they were late too often under [the local paratransit]'s operating system." (Rogers et al. 2021) Most paratransit programs also require reservations at least a day in advance, which can make

[6]Barrier to employment papers include: Lindsay 2011, Crudden and McBroom 1999, Field, Jette, and America 2007, Magill-Evans et al. 2008, Cook 2006, Edwards and Boxall 2010, Shier, Graham, and Jones 2009, Sundar et al. 2018, Hernandez et al. 2007, Meltzer, Robinson, and Fisher 2019, Graham, Inge, et al. 2018, Milfort et al. 2015.

last minute trips impossible. These limitations mean that typical public transportation or accessible paratransit may not always align with an individual's labor market or social needs. I contribute to the literature in this space by providing some of the first causal evidence on the impact of reliable and flexible transportation, through rideshare, on outcomes for people with disabilities. While most existing literature focuses on the impact of transportation on labor market outcomes, I go further to also consider the impact on social outcomes.

Reducing transportation barriers has the potential to improve a variety of outcomes for people with disabilities. Beyond the labor force, existing transportation barriers can limit social interactions and contribute to isolation for people with disabilities (Bascom and Christensen 2017; Bezyak, Sabella, Hammel, et al. 2020; Rintala et al. 1997). Improving transportation access would not only have individual benefits, such as increased income and personal fulfillment, but also contributes to the broader economy (Banks and Polack 2015; Saunders and Nedelec 2014). One such broader implication of improving transportation access is that the resulting increased labor force participation can lead to a reduction in dependency on social welfare programs. If improving access to transportation leads to a large enough reduction in public assistance, it may justify potential government intervention to help subsidize these types of transportation programs.

2.3 Uber

To understand the impact of improved transportation access, I focus on the changing availability of an on-demand and reliable transportation option during the 2010s, Uber. Uber provides a type of "reliability insurance," a fallback on-demand transportation option that can stand-in in case a person's usual method of transportation fails. The first Uber ride took place in San Francisco in 2010 and Uber expanded rapidly across the United States after that. By December 2016, they operated in 500 cities across the globe (Uber 2024). Uber users can request a pickup from the app and within minutes a driver will arrive to take them directly to their desired location. In this way, Uber's platform provides access to flexible on-demand transportation. Over time, as Uber expanded geographically, they also expanded their product offerings. UberBlack and UberX, which will be the focus of this paper, were typically the first of Uber's services to launch in a city and both allow customers to request

rides in private vehicles. Uber also has a wheelchair accessible option, UberWAV, which operates in a limited number of cities.[7] Outside of UberWAV, standard product offerings do not have any explicit accessibility requirements.

This is not the first paper to consider the broader impacts of Uber. Li, Hong, and Zhang (2018) and Khreis (2019) find that Uber's introduction in a city leads to a reduction in unemployment rates, particularly among "low skilled" individuals.[8] Both authors suggest that most of this employment growth is due to the *direct* effect of Uber, that is that people began driving for Uber, though they are unable to examine this directly with their city-level data and outcomes. I suggest that Uber's impacts could extend beyond just its driver-partners. Indeed, Uber could potentially have even larger impacts on the disabled population due to the lack of other reliable transit options, particularly for people with mobility or vision/hearing impairments. I use individual-level data to explore these claims and to examine impacts beyond the labor market.

Access to flexible on-demand transportation options can improve independence for people with disabilities, allowing them to seek and maintain employment more effectively. By providing reliable transportation, services like Uber can widen the geographic range accessible for employment, opening up new job opportunities that were previously unreachable. On-demand transportation may reduce dependency on less flexible paratransit services, and could more closely align with the spontaneous needs of daily life. Importantly, Uber is likely not taking the place of a person's usual method of transportation, and is instead providing a kind of "reliability insurance" in case another method falls through.[9] Services like Uber can also facilitate greater social engagement by making it easier to visit friends, participate in community events, and engage in recreational activities. This improved access to social

[7]The focus of this paper is on Uber's general product offerings but UberWAV and its effects are discussed in more depth in Section 4.4.

[8]Beyond employment, researchers have previously looked at how Uber impacted the taxi industry, public transportation, health behaviors, traffic incidents, local labor markets, driver-partner well-being, and more (Agrawal and Zhao 2023; Alvarez and Argente 2022; Anderson and Davis 2023; Angrist, Caldwell, and Hall 2021; Athey, Castillo, and Chandar 2024; Barreto, Mota Silveira Neto, and Carazza 2021; Berger, Chen, and Frey 2018; Berger, Frey, et al. 2019; Brazil and Kirk 2016; Brodeur and Nield 2018; Chaiyachati et al. 2018; Chang 2017; Chen, Chevalier, et al. 2019; Chen, Feinerman, and Haggag 2024; Christensen and Osman 2025; Dills and Mulholland 2018; Greenwood and Wattal 2017; Hall and Krueger 2018; Khreis 2019; Li, Hong, and Zhang 2018; Moskatel and Slusky 2019; Teltser, Lennon, and Burgdorf 2021).

[9]This is in line with the findings by Hall, Palsson, and Price (2018) who determine that Uber is commonly used as a complement rather than a substitute for traditional public transportation.

opportunities can enhance quality-of-life and overall well-being and lead to spillovers to the broader society.

I will extend the existing literature on transportation access by looking at the effects of reliable and flexible transportation on a vulnerable population that faces substantial barriers to other transportation options. I also extend my analysis beyond typical employment and health outcomes to consider a broader set of social outcomes.

3 Data and Methodology

3.1 Data

I obtained core-based statistical area (CBSA) Uber start date information from Hall, Palsson, and Price (2018)'s replication files, Teltser, Lennon, and Burgdorf (2021)'s appendix, and personal correspondence with Uber.[10] The earliest recorded Uber start date is in 2010, and the start date data are complete through 2022. My analysis relies on start dates for both UberBlack and UberX, and I determine treatment timing using the earliest available launch date for each city from any source. If UberX launched before UberBlack, that date is used, and vice versa. It is important to note that Uber's service was not always consistent in these cities; the replication data from Hall, Palsson, and Price (2018) includes exit and re-entry dates. For the purpose of this analysis, exit information is not considered. A city is counted as treated from the time of its first Uber launch.[11] As I do not have information on Uber's ridership, my analysis can be considered an intent-to-treat – measuring the impact of the transportation option being available rather than the impact of actual ridership.[12]

[10]CBSAs include both Metropolitan and Micropolitan Statistical Areas. According to the Census Bureau (2024), "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."

[11]Both Hall, Palsson, and Price (2018) and Teltser, Lennon, and Burgdorf (2021) argue that Lyft, Uber's primary competitor, tended to enter a city after Uber, but if this was not the case it would bias the analysis away from finding effects. Additionally, counting a city as being treated for all years after initial launch (by ignoring exit dates in the data), despite the fact that service may not have always been available during that time would also bias my results towards zero.

[12]Beyond data limitations, there is a conceptual reason to prefer availability over ridership as the treatment variable. Ridership is an equilibrium outcome as it reflects individuals' changing demand for transportation, which is itself shaped by the labor market and social outcomes this paper studies. Uber's availability, by contrast, is plausibly exogenous conditional on my specification, particularly given that roll-out was driven

The primary outcome data come from the Ruggles et al. (2024) Integrated Public Use Microdata (IPUMs) American Community Survey (ACS) spanning 2006 to 2019. This dataset contains individual-level data, which I link to Uber start dates using county identifiers. Due to privacy protections, not every observation in the public ACS includes a county identifier. For the years in my sample, I have approximately 460 identified counties in the data. Geographic information is exclusively available for counties with a population of 100,000 or larger, but as Uber is also primarily available in urban places, this limitation is unlikely to be a concern.[13] I restrict my sample to non-institutionalized prime age adults (22-54 year-olds) in order to focus on individuals who are more likely to be actively participating in the labor force or other socioeconomic activities where transportation accessibility could significantly impact their quality-of-life outcomes. Across all analyses, I use the person-level weights provided in the ACS.

My primary outcome measures - employment status, labor force participation, wages, public assistance, usual hours worked, and marital status - allow for a detailed analysis of the impact of improved transportation on the labor market, financial, and social outcomes for people with disabilities. While most outcomes are analyzed as binary variables, wages and hours worked are treated as continuous measures. Supplementary analyses also examine total income, information on household composition (divorce, living in a household with kids, living with an unmarried partner or living with ones parents), employment characteristics (indicators for working in a transportation occupation and being self employed), and changes in specific public assistance receipt (indicators for receiving any income from welfare, social security, or supplemental security income). I also examine the effects along the distribution of wages and hours worked, since the average effect might be hiding meaningful changes elsewhere in the distribution. To do this I create a series of binary variables equal to 1 if an individual earns above a certain threshold annually ($5,000, $20,000, or $30,000) or if they usually work at or above a certain number of hours each week (10 or 40). For outcomes such

largely by population size (Hall, Palsson, and Price 2018).

[13]As small cities with later launch dates are less likely to meet the population threshold necessary for identification in the ACS, my results should be understood as an effect in relatively large places, and may not extend to more rural areas. I find that counties that are part of Uber launch CBSAs but not present in the ACS data make up 17% of the total population impacted by Uber, revealing that I am capturing the majority of individuals impacted.

as hours worked and wages, I include people with zeroes in the analysis.

As described above, the American Community Survey measures disability status through a series of six questions. In my analysis I will consider a person "disabled" if they respond affirmatively to any of the six questions.[14] However, for more nuanced insights, I also conduct heterogeneity analyses across ages, disability types, and local public transportation quality.

3.2 Methodology

Uber rolled out at different times across the country, which is well-suited for a staggered difference-in-difference (DiD) approach. One robust empirical strategy for such a design is the stacked DiD design. Similar to other new difference-in-difference methods, the stacked DiD is robust to heterogeneous dynamic treatment effects. My data construction and analysis follow methods similar to those of Cengiz et al. (2019) and Deshpande and Li (2019). This method essentially compares cities with early adoption to those with later adoption by selecting a clean control group for each treatment cohort outside of a pre-specified event window. So the control group is composed of individuals in cities that are not-yet treated.

I rely on an event window of 4 pre-treatment years and 3 post-treatment years (including the event year). Within this framework, I create a separate dataset (or stack) for each cohort of Uber launch years. CBSAs that had a launch in a given year are considered treated, while CBSAs with a launch after the event window for that treatment cohort are used as control CBSAs. I then append each cohort-specific dataset together for the analysis. As an example of this set up, for CBSAs that launched in 2012 the control CBSAs are those that launched in 2015 or later, and I analyze the years 2008 to 2014 for all treated and control observations in this cohort.[15] This sample construction has the added benefit of addressing potential concerns about endogenous entry. Places with Uber are likely different on observables to places that never got Uber in these early years, and may vary in their disability employment trends. By comparing places that currently have Uber to places that eventually obtain Uber,

[14] Due to the similarity in the independent living and self-care questions, I combine these categories in my analysis. The broad categories of disability I examine are vision/hearing, mobility, cognitive and self-care limitations.

[15] Maps documenting the identifying variation for each treatment cohort are presented in Figures D1 through D7.

I reduce the possible bias associated with endogenous entry. In the following sections I will provide further evidence to support this.

The main specification is as follows:

$$Y_{icts} = \alpha_{cs} + \gamma_{ts} + \sum_{\substack{e=-4 \\ e\neq -1}}^{2} \beta_e \left(\mathbf{1}[e_{cts} = e] \times \text{Treat}_{cs}\right) + \epsilon_{icts} \tag{1}$$

where Y_{icts} is the outcome for individual i in CBSA c at year t in sub-experiment s, α_{cs} are CBSA $\times$ sub-experiment fixed effects, and γ_{ts} are year $\times$ sub-experiment fixed effects. Treat_{cs} is an indicator equal to one if CBSA c is a treated unit in sub-experiment s, and e_{cts} denotes event time (the number of years relative to Uber's launch in CBSA c) with $e = -1$ serving as the omitted reference period. The coefficients of interest are the β_e, which trace out the dynamic treatment effects of Uber's availability at each point in the event window. Standard errors are clustered at the CBSA level. All models are estimated using weighted least squares, where the weights combine the ACS person weight with a corrective stack weight derived following Wing, Freedman, and Hollingsworth (2024).[16] For ease of presentation, the main tables report a single summary coefficient, $\hat{\beta} = \frac{1}{3}\sum_{e=0}^{2} \hat{\beta}_e$, the simple average of the three post-period event-time coefficients, with the full set of event-time estimates presented graphically in the event study figures.

In the robustness section below I investigate concerns of internal validity in depth. The primary identifying assumption is that of parallel trends, that the outcomes in places that received access to improved transportation would have continued evolving similarly to their control group in the absence of Uber. I provide visual evidence, in the form of event studies, that the parallel trends assumption is not violated (Figure 1).[17] I also show that the overall pattern of results holds with the inclusion of geographic or individual-level controls and other alternative specifications.

[16] The corrective stack weight re-balances the implicit weights applied to treatment and control trends across sub-experiments, ensuring that the weighted stacked estimator identifies the trimmed aggregate average treatment effect on the treated.

[17] Event study plots for all supplemental outcomes can be found in the Appendix (Figures D8 and D9).

4 Results

The availability of flexible and reliable transportation, such as Uber, leads to significant improvements in outcomes for people with disabilities. In this section, I examine the effects of the availability of Uber on a range of quality-of-life outcomes for this population.[18] I also explore how these effects may vary across different subgroups of the disabled population. Since disability is not a one-size-fits all description I will look at heterogeneity across different types of self-reported disability as well as across age and other demographic groups. My analyses focus primarily on prime age adults (22-54) as this population are more likely to engage with the labor force.

Improved access to transportation leads to significant improvements in quality-of-life outcomes for people with disabilities, as evidenced by the analysis summarized in Table 2. Access to improved transportation generates significant increases in labor force engagement, with a 1.2 percentage point (3%) increase in employment, however this is not accompanied by an statistically meaningful increase in labor force participation. This implies that while Uber improves employment outcomes, it is mostly among individuals who were already looking for work. Consistent with this extensive margin effect on employment, there is also an intensive margin effect on usual hours worked per week. The baseline average usual hours worked is low for this population (15 compared to 32 for people without disabilities), due to the high number of people with zero hours worked, but Uber's entry increases hours worked by about 3% on average.

Following access to improved transportation, annual wages also rise by about $576 (nearly 5%). While statistically meaningful, this average effect on wages may be hiding effects along the wage distribution and to explore this further, I produce estimates using binary outcomes for earning above certain thresholds. Comparing Table 2 to Table 3 there is a nearly identical percentage point increase in employment as in the share of people earning over $5,000 a year. There is a slightly smaller increase for people earning over $20,000, and almost no increase in

[18] While the focus of this paper is on people with disabilities, results for the broader population can be seen in Appendix B. In summary, I confirm the positive employment effects of Uber's availability that Li, Hong, and Zhang (2018) and Khreis (2019) find. I also find small effects on marriage. Using a triple difference-in-difference design, I show that these effects are all larger among prime age people with disabilities relative to people without disabilities.

people earning over $30,000 indicating that much of the increase in employment was driven by jobs that paid quite low earnings. I also look along the distribution of hours worked using a similar approach. Again comparing Table 2 to Table 3, it is clear that much of this employment increase was among individuals working full time, or at least 40 hours per week. This increase could be due to people who switched from being unemployed to now working full time, or it could be that improved access to transportation allowed some people who were already employed to work more hours.

A potential underlying mechanism for these results could be that all of the employment growth is due to people working for Uber, as Li, Hong, and Zhang (2018) and Khreis (2019) suggest. In Table 3 we see there is a slight uptick in the percent of disabled adults who are self employed but this coefficient is nowhere near the magnitude of the main employment effects. There is also no change in people working in transportation-related occupations. While Bracha and Burke (2021) make it clear that traditional surveys are often ill-equipped to capture gig work, it does not appear that driving for Uber is driving these results.

The relationship between improved transportation access and public assistance receipt is more nuanced. As shown in Figure 1e, there is a marginally statistically significant decline in public assistance receipt in the first year following Uber's introduction (p-value = 0.088), but this effect is temporary and reverts in subsequent periods. Averaging across the post-period, the effect is a small and statistically insignificant reduction of 0.7 percentage points, or 2.8% (Table 2). Unlike studies that focus on factors that have increased the reliance of disabled individuals on public assistance in recent years, the availability of flexible and reliable on-demand transportation appears to generate at least a short-run reduction in reliance on public assistance as barriers to active labor force engagement are removed. Table 4 shows that this pattern, while imprecise, is concentrated in Supplemental Security Income (SSI) and welfare, which is consistent with what one would expect for this population given the close link between SSI eligibility and labor force attachment. Notably, total income exhibits a statistically significant increase of approximately $607 per year, suggesting that while individuals may be temporarily transitioning off public assistance, the wage gains associated with increased employment are leading to higher total incomes on average.

The availability of reliable and flexible transportation may also increase opportunities

for social interaction, either by facilitating mobility to social events directly or by indirectly increasing opportunities for or interest in social engagement due to increased employment. Following the introduction of Uber, I find that marriage rates among people with disabilities increased by 2.3 percentage points, or nearly 6% (Table 2). In Table 4, I find that divorce rates decline following the introduction of Uber to an area - perhaps driven by reductions in financial strain or caregiving responsibilities.[19] This is one possible mechanism behind the observed increase in marriage rates, as reductions in the probability of divorce mechanically increase the share of the population that remain married. Another potential explanation for the observed effect on marriage simply that gaining a new flexible and reliable transportation option gives individuals increased access to people, places, and social events. We know from Teltser, Lennon, and Burgdorf (2021) that access to Uber leads to increased binge drinking among the broader population, some of which occurs in bars. This may be true among this population as well, and would represent increased social opportunities. I explore effects on other household composition measures in Table 4 - including living in a household with children, living with ones parents, and living with an unmarried partner and find no evidence of precise impacts on any other outcomes. Overall, either through increased access to social events or through reductions frictions that lead to divorce, I find evidence that Uber led to improved social inclusion.

4.1 Heterogeneity by Demographic Groups

Understanding how the effects of access to reliable and flexible transportation vary by age is important because different age groups likely experience distinct transportation needs and labor market opportunities. Prime-age individuals (22-54) are more likely to be actively engaged in the workforce, making them particularly sensitive to improvements in transportation access. Conversely, older adults (55-67) may benefit more from social engagement opportunities, given their declining labor force participation.

The largest labor market and social effects are indeed observed among prime-age (22-54

[19]The relationship between economic conditions and marital stability is not unique to this setting. Slusky and Ginther (2021) find that the ACA's Medicaid expansion reduced divorce rates among college-educated adults aged 50–64, suggesting that alleviating financial strain more broadly can stabilize marriages.

years old) adults, shown in Table D2. These findings indicate that this age group, likely with higher transportation needs related to employment and social activities, benefits substantially from improved transportation options. There are no statistically meaningful impacts on labor market or social outcomes for young adults (16-21) or older adults (55-67).

The effects on employment and marriage differ slightly across other demographic groups including race, educational attainment, and gender, although some of the effects are imprecise. As shown in Appendix Tables D3 and D4, employment effects are concentrated among non-white, male, and individuals without a college degree. Whereas effects on marriage are similar in magnitude across gender, and mostly concentrated among white individuals.

4.2 Heterogeneity by Disability Type and Transportation Access

Examining whether the effects of improved transportation vary by type of disability is also a crucial exercise in order to fully understand these results, as some disability groups may experience greater barriers to both employment and mobility. Specifically, disabilities related to vision or hearing may hinder physical access to work, but not necessarily the functional ability to work itself, whereas cognitive or self-care limitations may present more substantial barriers to labor force participation regardless of transportation availability. Traditionally, people with different types of disabilities also face different barriers to transportation. As shown in Bascom and Christensen (2017) for the disability types in this paper, 70% of people with hearing difficulties use their own vehicle as their primary transportation, but for all other disability types 50% or more report their primary mode of transportation is something other than their own vehicle (including buses, paratransit, or getting rides with others).

Due to the prevalence of public transportation use among this population, I also examine heterogeneity by the quality of local public transportation, as it is possible that improving access to transportation may have larger effects in places with worse existing public transportation options. To do this I rely on the Transit Connectivity Index by the Center for Neighborhood Technology (2019). In broad terms, this index attempts to measure how well-connected a household is to the local public transportation system in terms of proximity. I divide geographies into places with above median transit connectivity (considered better local

public transportation) and below median connectivity (worse local public transportation).

The subgroup analysis by disability type (Table D5 and Figures 3 and 5) reveals that individuals with vision/hearing disabilities do experience the most significant improvements in outcomes across the board. They see a 1.9 percentage point increase (4.4%) in employment and a nearly 3 percentage point (5.5%) increase in marriage rates. This fact is interesting given that baseline levels of many outcomes are also higher across the board for this subgroup.

This pattern of results indicates that Uber's employment effects are mostly concentrated among those who are more highly attached to the labor market to begin with. For individuals with self care or cognitive limitations, improving access to transportation may not be enough to overcome barriers to employment. Uber's positive effect on marriage can be observed across individuals of all disability types. Still, improved transportation's impact on social outcomes seems to be more consistent across different disability types and is even present among groups that did not experience significant changes in employment.

I further explore how the effects of reliable and flexible transportation may vary based on the quality of local public transportation, as measured through the Transit Connectivity Index by the Center for Neighborhood Technology. The results (Table D6 and Figures 3 and 5) reveal a nuanced pattern: employment effects are concentrated in places with better local public transportation, consistent with Hall, Palsson, and Price (2018)'s finding that rideshare tends to complement rather than substitute for existing transit. Where some infrastructure already exists, Uber appears to fill reliability gaps that enable labor force participation at the margin. Marriage effects, on the other hand, are concentrated in places with worse local public transportation, suggesting that in areas of severe transit scarcity, improved access may primarily expand social participation rather than employment opportunities.

4.3 Threats to Internal Validity and Robustness

As with any empirical design, it is crucial to address potential threats to the internal validity of these estimates. Below, I discuss the major threats in decreasing order of concern and present various robustness checks that mitigate concerns regarding these issues.

A primary concern in a difference-in-differences approach is the potential violation of the parallel trends assumption. In this case, Uber's entry may have been strategically timed,

targeting larger cities first, which may trend differently due to their economic characteristics. If Uber's entry *was* strategically timed in order to target places that already had strong labor forces or overall better outcomes for people with disabilities, one might expect to see that treated places were trending differently on the outcomes in this study, in which case the event study plot would have an upward slope in the pre-period and the confidence interval would not overlap with zero. This is not the case. I have provided event study figures for all of the main and supplementary outcome variables. The event study figures (Figure 1) visually support that the parallel trends assumption is not violated in this context - with no significant pre-treatment deviations observed across any of the main outcomes.[20]

While the visual evidence suggests that the parallel trends assumption is not violated, I also check for endogenous timing by adding a lagged treatment indicator, which examines whether outcomes were already trending before Uber's introduction. This is done by adding an indicator variable to the primary specification which takes a value of 1 in the year prior to treatment for that CBSA. The coefficients on the "Treat Next Year" variable, in Table 5, are statistically insignificant and close to zero, supporting the assumption that Uber's entry was not driven by prior trends in the outcome variables. Additionally, I am unable to predict the timing of Uber's entry with my lagged outcome variables. For this analysis, the unit of observation is a CBSA, the outcome is the year they received Uber and the independent variable is the outcome (disability employment rate, disability marriage rate, disability share of the population etc) in the year prior to Uber's launch. Table D7 presents these results. On average, places with higher labor force participation rates received access to Uber a bit earlier, but there is no consistent sign across these results. Places with higher employment rates, marriage rates, average usual hours worked, and disability share of the prime age population and lower public assistance are associated with later launch dates, but places with higher labor force participation and wages tend to get Uber earlier. However, importantly, there is no statistical evidence that the lagged primary outcomes predict the timing of Uber's entry. This aligns with findings from Hall, Palsson, and Price (2018), who report that Uber's roll-out strategy was largely influenced by population size rather than labor market conditions.

[20] Event study figures for the supplemental outcomes can be found in the appendix, Figures D8 and D9.

A second potential threat is that the introduction of Uber could have induced differential migration or other compositional changes, which might bias the estimates. To address this concern, I examine whether the introduction of Uber affected migration patterns or the disability composition of cities in Table D8. First, I test for any changes in the prevalence of disability after Uber's introduction. The results show no meaningful changes in disability prevalence, ruling out the possibility that changes in the disability composition of cities are driving the results. This finding is twofold, access to transportation does not cause people to respond differently to questions about disability status, and it is unlikely that Uber led to an increase in the share of people with disabilities in cities for which Uber was available. I test the second claim more directly by examining whether the introduction of improved transportation led to increased migration for people with disabilities into treated cities. The estimated effect on migration (in column 2) is close to zero, indicating that migration is also unlikely to be a confounding factor in this analysis.

To further address concerns about compositional changes, I provide results for a model that includes CBSA-level controls. These controls include: population (from the Census), personal income per capita (from the Bureau of Economic Analysis), and the median home price index (from the Federal Housing Finance Agency). The inclusion of these controls can be seen in the second panel of Table 5. Qualitatively, the results hold, however the effects lose precision, becoming marginally insignificant. One such example is employment which now has a p-value of 0.105.

Finally, the pre-treatment period for my earliest cohorts overlaps with the aftermath of the Great Recession, raising concerns that changing labor market conditions may confound the estimates. To mitigate this concern, I re-estimate the main results after excluding the earliest cohort (2010). These are also some of the largest treated cities, so this robustness check also serves to alleviate concerns that these results are simply a phenomenon of big cities. The results, shown in Table 5, confirm that the main effects remain robust even after dropping this early treatment cohort. Overall, my main findings are robust to a variety of different specification choices.

Table 6 presents a final set of robustness checks addressing three additional potential confounds. The first panel restricts the sample to states that ever expanded Medicaid eligi-

bility under the Affordable Care Act, a process that occurred during the same time frame as Uber's roll out. Because Medicaid expansion disproportionately affected low-income individuals with documented health conditions and because expansion timing is correlated with early UberX entry in several states, it is important to verify that the main results are not driven by differential changes in health insurance access. Restricting to explore variation only within Medicaid expansion states, the effects on employment and marriage remain positive and statistically significant, suggesting that Medicaid expansion is not driving the main findings.

The second panel of Table 6 addresses a potential confound arising from changes in how the ACS coded same-sex marriages prior to 2013, whereby same-sex married couples were recoded as unmarried. Because LGBTQ individuals report higher rates of disability (Surfus 2023) and because UberX entered cities with large LGBTQ populations relatively early, this coding change could spuriously inflate estimated marriage effects in treated areas. Omitting individuals in same-sex marriages or partnerships from the sample, the results are substantively unchanged, alleviating concerns that the marriage effect reflects this reclassification rather than a genuine behavioral response to Uber availability.

The third panel of Table 6 isolates variation from UberX launches only, setting aside the UberBlack entries that account for many of the earliest treatment cohorts in the main analysis. Because UberBlack operates as a premium limousine service, its relevance for a low-income, disability population is less clear, and a cleaner test of the mechanism focuses on the more accessible and affordable UberX product. Unfortunately, data that separate out launch dates by type of service are only available through the 2014 treatment cohort, and the sample size falls accordingly. Within this restricted sample, however, the effects are strong and precisely estimated across all outcomes, with point estimates that are somewhat larger in magnitude than the main results, a story consistent with UberX representing the more relevant margin of access for this population. A large caveat, however, is that Uber offered artificially lower cost trips in the early years of UberX service and as prices rise, these effects may taper off slightly.

4.4 UberWAV

Uber's main offerings, which have been the primary focus of this paper, are not required to be physically accessible to people with disabilities. UberWAV is Uber's wheelchair accessible vehicle program which first launched in Chicago in March 2014. All WAV drivers receive a third party certification in safely driving and assisting people with disabilities. While this service does not operate across many cities in the United States, it could have even larger impacts on quality-of-life for people with disabilities. I discuss UberWAV cities and the empirical strategy for this analysis in more detail in Appendix C.

Appendix Table C2 presents the results from a standard two-way fixed effects model.[21] Overall, UberWAV had very small statistically insignificant effects across all outcomes. A zero in this context does make sense, however. UberWAV launched *after* UberX or UberBlack in all of these cities so it may be that people with disabilities were already induced into the labor market or into greater social connections with the more standard product offerings. While UberWAV may be a more convenient and accessible service, providing an important transit option for people with disabilities, people may have already changed their behavior in response to the initial services in their cities. Additionally, UberWAV may have differential impacts outside of my primary sample of 22-54 year olds. In the appendix I explore the differential effects of UberWAV in more detail.

4.5 Policy Implications

Improving access to reliable and flexible transportation through services like Uber alleviates a meaningful barrier that people with disabilities face and leads to widespread benefits beyond just the disability community. Increased government revenues through income taxes as well as potentially reduced caregiving needs and utility from social connectedness are all benefits to Uber access that are not borne directly by the transportation provider. To the extent that rideshare companies do not internalize these broader social benefits, they may under-provide services to the disability community relative to what would be socially optimal. Prior to

[21] Note that this is a simple 2x2 TWFE with one pre-period year and one post-period restricted to only evaluate the effect in cities that gained access in 2014. Cities that do not yet have UberWAV are used as the control group. Due to the small number of cities that have rolled out this program, there is only a one year post-period so I cannot use a stacked difference in difference approach.

the introduction of rideshare services, traditional public transportation systems struggled to provide options that meet the unique needs of this population, leading to underemployment and higher rates of reliance on government assistance programs. The rise of ridesharing technology offers a partial solution, though its availability is mostly limited to urban and more densely populated areas where people with disabilities are still reliant on traditional, often unreliable, transportation services. Ridesharing is also costly relative to other forms of public transportation, which raises the question of whether the government should actively intervene to expand access for people with disabilities.

Whether intervention through price reductions would meaningfully increase rideshare use among this population depends in part on the price elasticity of demand. Existing estimates for the general population find that rideshare demand is inelastic (Cohen et al. 2016), but to my knowledge no study has yet estimated price elasticity of rideshare demand specifically by disability status or income, making this an important avenue for future work.

While providing direct subsidies for ridesharing may bring moral hazard concerns such as over-utilization or misuse, it is worth noting that the government already provides federal subsidies to paratransit services, which on average cost substantially more per ride than Uber (Shared Use Mobility Center 2016). In Boston's MBTA pilot, for example, traditional paratransit trips cost an average of $59 per trip compared to just $9.10 for TNC trips (U.S. Department of Transportation, ITS Knowledge Resources 2019). While in other cities costs may differ, paratransit rides routinely cost around $30-40 per trip (Shared Use Mobility Center 2016). Survey evidence suggests that people with disabilities who use rideshare take approximately five trips per month (Federal Highway Administration 2022), meaning the per-ride cost differential alone suggests that substituting rideshare for traditional paratransit could reduce costs to public transit agencies while improving service flexibility. Some cities have already begun moving in this direction, with Boston, Green Bay, Fort Worth, and New York City launching public-private partnerships that offer subsidized on-demand rideshare as part of their paratransit programs

One limitation of this argument, however, is that it abstracts away from general equilibrium effects. If these partnerships make rideshare trips available at a reduced out-of-pocket cost, this is likely to increase overall rideshare demand, which could put upward pressure on

prices and diminish the fiscal savings from replacing traditional paratransit. The supply side of rideshare markets does respond relatively quickly to changes in demand conditions (Hall, Horton, and Knoepfle 2023), which may limit the extent of price increases in practice, but the net effect remains an open question. Rigorous evaluation of existing public-private partnership models would be a valuable contribution to understanding whether such interventions can deliver the improvements in transportation access documented here at reasonable cost.

5 Discussion

People with disabilities face significant barriers to economic and social inclusion, and transportation is one of the most critical yet overlooked obstacles. Reliable and flexible transportation is necessary for participation in the labor market, access to essential services, and engagement in social activities. In this paper, I explore the extent to which improved transportation access can address these barriers, using Uber's introduction to understand how important this particular barrier might be.

My results show that better access to transportation leads to meaningful improvements in labor market outcomes and social integration, along with temporary declines in public assistance receipt. Employment rates increase for people with disabilities after the introduction of Uber (3%), hours worked and wages also rise, though deeper dives into the distributions reveal these are mostly full time, lower wage jobs. Through supplemental analyses I can rule out that this employment increase is solely caused by the direct employment effect of the rideshare service, as suggested by other studies.

Heterogeneity analysis further emphasizes that not all people with disabilities experience the same benefits from improved transportation. Those with vision or hearing impairments, who are less likely to report having barriers to transportation, show the largest gains in employment and social engagement. On the other hand, individuals with cognitive or self-care limitations see smaller improvements, which suggests that transportation alone is not sufficient to overcome the broader challenges they face in securing employment. This implies that while transportation is a critical component to inclusion, it is not a panacea. Other barriers still need to be addressed for certain subgroups within the disabled population.

It is important to remember that the impacts of Uber likely represent a lower bound for the potential benefits of improved transportation access. While Uber provides more flexibility than traditional public transit or paratransit services, it is still an expensive option, particularly for low-income individuals, including many people with disabilities who rely on public assistance. If costs were lower, ridership might increase and effects could be even larger. The high costs may also explain why, when compared to transportation-access related interventions for other populations, the effects seen here are markedly smaller in magnitude at 3%. Effect sizes across a variety of other studies range from 0 to 59%, with most studies reporting effects above 10%.[22] The smaller observed effect sizes among people with disabilities also provides support for the argument that while transportation access is a crucial barrier to employment for this population, it is not the only barrier that this group faces.

The implications of these findings extend beyond Uber or ridesharing services. If improved transportation can help people with disabilities engage more fully in the workforce and improve their social connectedness, there is potential for significant economic and social gains. Policymakers may want to consider how to expand access to reliable, flexible, and affordable transportation options for people with disabilities, especially in areas where public transit options are limited. Subsidizing ridesharing services or expanding public transportation infrastructure could help alleviate one of the major barriers preventing people with disabilities from fully participating in society.

Overall, these results highlight the importance of transportation as a key barrier to economic and social participation for people with disabilities. By addressing this barrier, we can unlock significant potential for improved outcomes in employment, income, and social integration. However, while Uber alleviates one barrier, there are still other non-transportation related barriers that people with disabilities face and those will need to be addressed in order to further support broader economic and social inclusion.

[22]Papers included in this review are: Åslund, Blind, and Dahlberg (2017), Bollinger and Ihlanfeldt (1997), Gurley and Bruce (2005), Kim (2019), Li and Wyczalkowski (2023), Mayer and Trevien (2017), Pasha et al. (2020), Raphael and Rice (2002), and Tyndall (2017, 2021).

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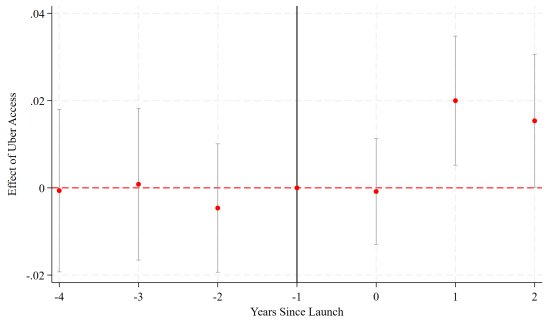
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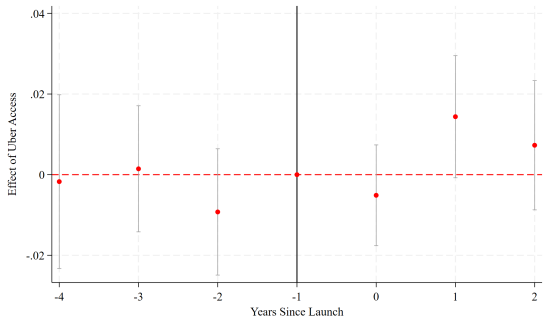
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Tables and Figures

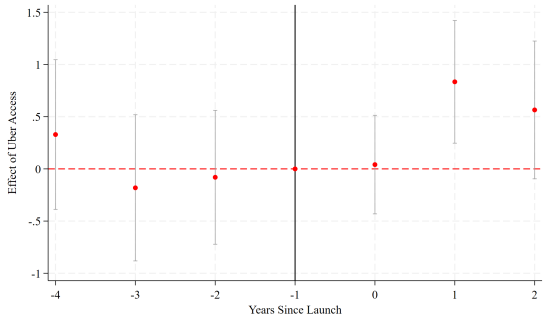
Figure 1: Event Studies - Main Outcomes



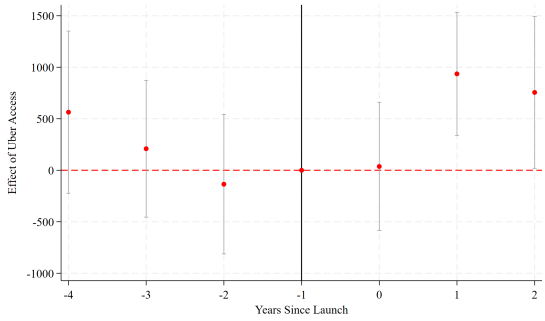
(a) Employment



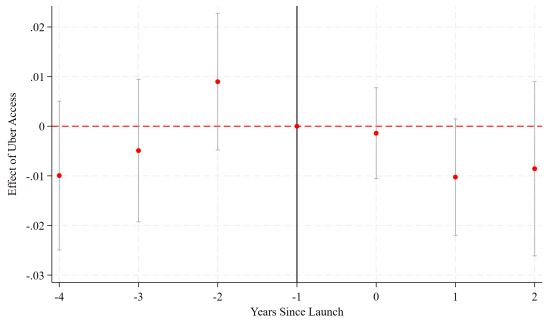
(b) Labor Force Participation



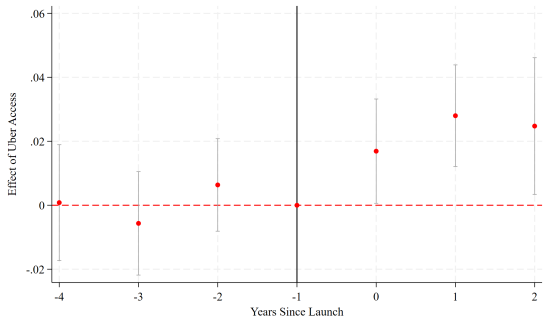
(c) Usual Hours Worked



(d) Wages



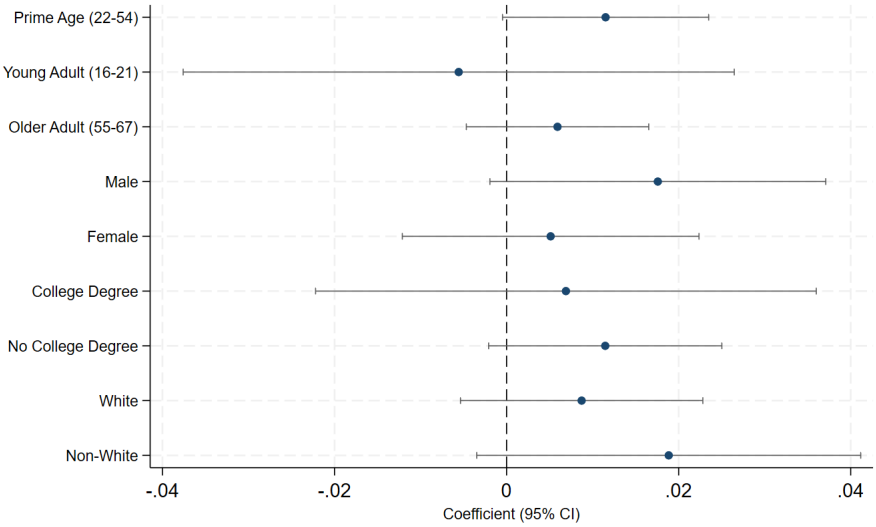
(e) Public Assistance



(f) Married

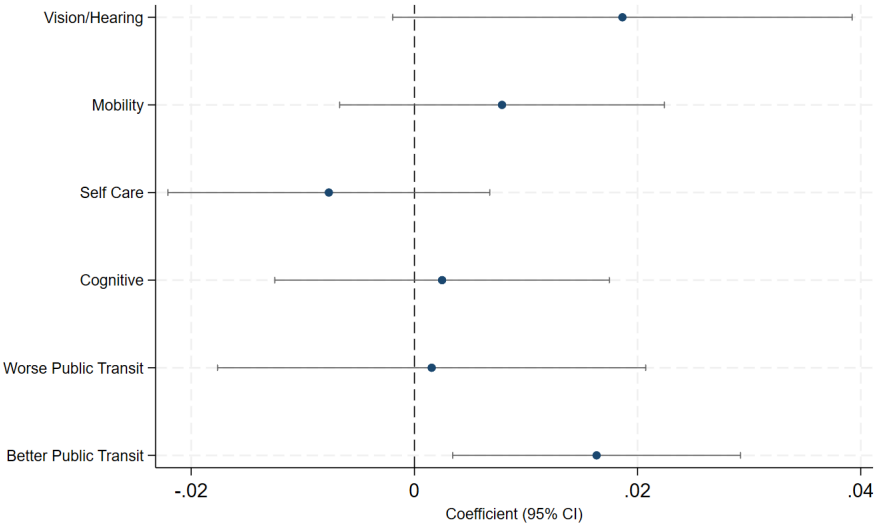
Note: Data are from the American Community Survey, restricted to individuals who report having a disability. Standard errors are clustered at the CBSA-level. Figures presents coefficients and 95% confidence intervals from an event study specification. Coefficients in all time periods are relative to the year prior to launch where time = 0 is the year of Uber's launch in the treatment group. Employed is a binary variable = 1 if an individual is employed, labor force participation is a binary variable = 1 if an individual is in the labor force, usual hours worked are equal to the usual hours an individual works per week, wages are equal to annual income from wages, public assist is a binary variable =1 if a person receives any income from public assistance, and married is a binary variable = 1 if the individual is married.

Figure 2: Demographic Heterogeneity: Employment



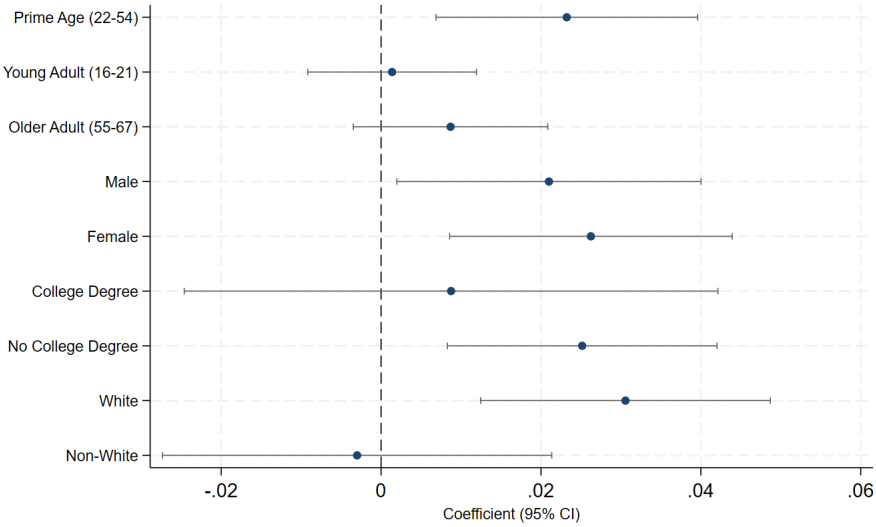
Note: Data are from the American Community Survey, restricted to individuals who report having a disability, 2006-2019. Standard errors are clustered at the CBSA-level. All models use equation (1). Outcome is a binary measure = 1 if an individual is employed and zero otherwise. Each row reports the coefficient on the linear combination of the post-launch coefficients in a model that only includes the subgroup listed on the y-axis.

Figure 3: Disability Heterogeneity: Employment



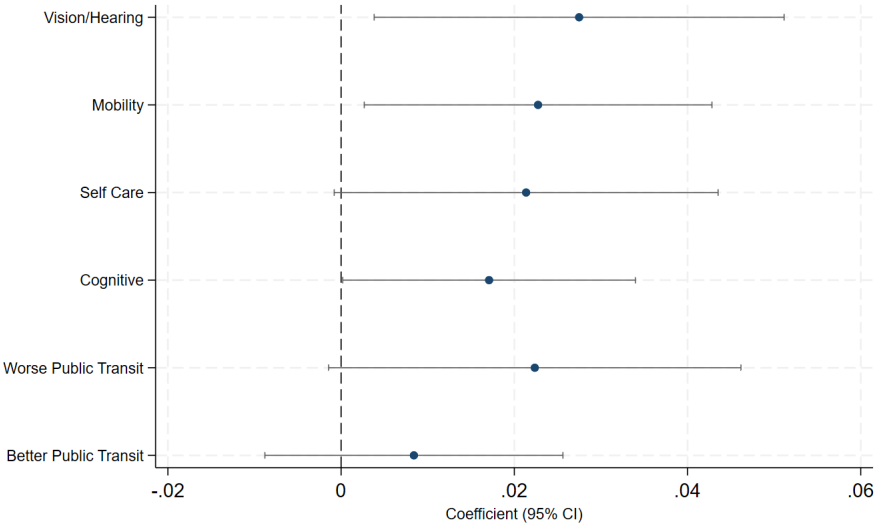
Note: Data are from the American Community Survey, restricted to individuals who report having a disability, 2006-2019. Standard errors are clustered at the CBSA-level. All models use equation (1). Outcome is a binary measure = 1 if an individual is employed and zero otherwise. Each row reports the coefficient on the linear combination of the post-launch coefficients in a model that only includes the subgroup listed on the y-axis.

Figure 4: Demographic Heterogeneity: Marriage



Note: Data are from the American Community Survey, restricted to individuals who report having a disability, 2006-2019. Standard errors are clustered at the CBSA-level. All models use equation (1). Outcome is a binary measure = 1 if an individual is married and zero otherwise. Each row reports the coefficient on the linear combination of the post-launch coefficients in a model that only includes the subgroup listed on the y-axis.

Figure 5: Disability Heterogeneity: Marriage



Note: Data are from the American Community Survey, restricted to individuals who report having a disability, 2006-2019. Standard errors are clustered at the CBSA-level. All models use equation (1). Outcome is a binary measure = 1 if an individual is married and zero otherwise. Each row reports the coefficient on the linear combination of the post-launch coefficients in a model that only includes the subgroup listed on the y-axis.

Table 1: Summary Statistics by Disability Status

	Any Disability	No Disability
Employment Rate	0.421	0.807
	(0.494)	(0.394)
Labor Force Participation	0.500	0.861
	(0.500)	(0.346)
Wage Income	15,797	40,767
	(32,530)	(54,491)
Total Income	22,565	44,721
	(35,355)	(58,699)
Share with Public Assistance	0.229	0.020
	(0.420)	(0.140)
Age	40.984	37.644
	(9.658)	(9.482)
Share with at Least a College Degree	0.150	0.360
	(0.357)	(0.480)
Share Moved in Last Year	0.173	0.176
	(0.378)	(0.381)
Share Living in a HH with Kids	0.346	0.474
	(0.476)	(0.499)
Share Living with Parents	0.209	0.136
	(0.406)	(0.343)
Share Married	0.356	0.528
	(0.479)	(0.499)
Share with Self Care or Independent Living Disability	0.388	
	(0.487)	
Share with Mobility Disability	0.455	
	(0.498)	
Share with Vision/Hearing Disability	0.314	
	(0.464)	
Share with Cognitive Disability	0.461	
	(0.498)	
Observations	777,028	9,734,554

Note: Data are from the American Community Survey 2006-2019. The sample is restricted to individuals age 22-54. Standard deviations in parentheses.

Table 2: Main Results - Full Sample

	(1) Employed	(2) Labor Force	(3) Usual Hours	(4) Wages	(5) Public Assistance	(6) Married
Uber Available	0.012*	0.006	0.480*	575.962**	-0.007	0.023***
	(0.006)	(0.006)	(0.251)	(261.038)	(0.005)	(0.008)
Observations	963,494	963,494	963,494	963,494	963,494	963,494
Control Mean†	0.390	0.475	14.723	11,965.925	0.245	0.385

Note: Table uses individual-level data from the 2006-2019 American Community Survey. Sample restricted to individuals age 22-54 who reported having any disability. Standard errors are clustered at the CBSA-level. All models use equation (1) and include fixed effects for CBSA and year, interacted with sub-experiment cohort. Employed is a binary variable = 1 if an individual is employed, labor force is a binary variable = 1 if an individual is in the labor force, usual hours worked are equal to the usual hours an individual works per week, wages are equal to annual income from wages, public assist is a binary variable =1 if a person receives any income from public assistance, and married is a binary variable = 1 if the individual is married. †The control mean reports the mean of each outcome in the pre-period years for the control observations in each cohort. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3: Supplemental Employment Results

	(1) Wages ≥ 5,000	(2) Wages ≥ 20,000	(3) Wages ≥ 30,000	(4) Hours ≥ 10	(5) Hours ≥ 40	(6) Occ: Transport	(7) Self Emp
Uber Available	0.010*	0.008*	0.004	0.012*	0.012**	0.001	0.003
	(0.006)	(0.005)	(0.004)	(0.006)	(0.005)	(0.003)	(0.003)
Observations	963,494	963,494	963,494	963,494	963,494	963,494	963,494
Control Mean†	0.374	0.226	0.154	0.379	0.252	0.057	0.052

Note: Table uses individual-level data from the 2006-2019 American Community Survey. Sample restricted to individuals age 22-54 who reported having any disability. Standard errors are clustered at the CBSA-level. All models use equation (1) and include fixed effects for CBSA and year, interacted with sub-experiment cohort. Wage variables are binary variables = 1 if a person earns over the amount listed, hours variables are binary measures = 1 if an individual usually works more than the amount listed per week, Occ. Transport is a binary variable = 1 if an individual is employed in a transportation-related occupation. Self Emp is a binary variable = 1 if an individual reports being self-employed. †The control mean reports the mean of each outcome in the pre-period years for the control observations in each cohort. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4: Supplemental Income and Household Composition Results

	(1) OASDI	(2) Welfare	(3) SSI	(4) Total Income	(5) Kids	(6) Live with Parents	(7) Unmarried Partner	(8) Divorced
Uber Available	0.000	-0.003	-0.003	606.974**	0.010	0.008	-0.002	-0.007*
	(0.005)	(0.004)	(0.006)	(298.929)	(0.007)	(0.006)	(0.003)	(0.004)
Observations	963,494	963,494	963,494	963,494	963,494	963,494	963,494	963,494
Control Mean†	0.192	0.065	0.201	18,549.79	0.361	0.173	0.076	0.185
CBSA and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Table uses individual-level data from the 2006-2019 American Community Survey. Sample restricted to individuals age 22-54 who reported having any disability. Standard errors are clustered at the CBSA-level. All models use equation (1) and include fixed effects for CBSA and year, interacted with sub-experiment cohort. OASDI is a binary variable = 1 if an individual receives any income from social security, Welfare is a binary variable = 1 if an individual receives any income from welfare, SSI is a binary variable = 1 if an individual receives any income from supplemental social security, Total Income is equal to the annual total personal income, Kids is a binary variable = 1 if an individual lives in a household with children, Live with Parents is a binary variable = 1 if the individual reports living in a household with their parents, Unmarried Partner is a binary variable = 1 if an individual reports living in a household with their unmarried partner. Divorce is a binary variable = 1 if an individual is divorced. †The control mean reports the mean of each outcome in the pre-period years for the control observations in each cohort. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 5: Main Robustness Checks

	(1) Employed	(2) Labor Force	(3) Usual Hours	(4) Wages	(5) Public Assistance	(6) Married
Includes Lagged Timing						
Uber Available	0.016**	0.015**	0.560*	711.409**	-0.016**	0.017**
	(0.007)	(0.007)	(0.315)	(317.258)	(0.007)	(0.008)
Uber Available Next Year	0.005	0.009	0.080	135.446	-0.009	-0.006
	(0.008)	(0.008)	(0.327)	(344.947)	(0.007)	(0.007)
Observations	963,494	963,494	963,494	963,494	963,494	963,494
Includes Geographic Controls						
Uber Available	0.011	0.003	0.451	422.993	-0.007	0.024**
	(0.007)	(0.007)	(0.279)	(290.106)	(0.006)	(0.010)
Observations	962,307	962,307	962,307	962,307	962,307	962,307
Drop Earliest Cohort						
Uber Available	0.011*	0.005	0.454*	559.780**	-0.006	0.023***
	(0.006)	(0.007)	(0.255)	(265.120)	(0.006)	(0.008)
Observations	704,842	704,842	704,842	704,842	704,842	704,842

Note: Data are from the American Community Survey, restricted to individuals age 22-54 who report having a disability. Standard errors are clustered at the CBSA-level. All models except the lagged timing use equation (1) and include fixed effects for CBSA and year, interacted with sub-experiment cohort. the specification for lagged timing shifts the reference pre-period to be two periods prior to treatment, in order to report the coefficient on one year prior to treatment. Employed is a binary variable = 1 if an individual is employed, labor force is a binary variable = 1 if an individual is in the labor force, usual hours worked are equal to the usual hours an individual works per week, wages are equal to annual income from wages, public assist is a binary variable =1 if a person receives any income from public assistance, and married is a binary variable = 1 if the individual is married. Uber Available Next Year is an indicator equal to 1 if the observation is in a city that will receive Uber next year. In the model with controls: geographic controls include: population, personal income per capita, and the median house price index. A small number of geographies were not available for all control measures, reducing the sample size slightly. The sample for the panel that removes early cohorts excludes the 2010 treatment cohort. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6: Robustness Check: Alternative Samples

	(1) Employed	(2) Labor Force	(3) Usual Hours	(4) Wages	(5) Public Assistance	(6) Married
Only Medicaid Expansion						
Uber Available	0.011*	0.007	0.433	480.927*	-0.003	0.018***
	(0.007)	(0.007)	(0.264)	(277.975)	(0.006)	(0.007)
Observations	684,862	684,862	684,862	684,862	684,862	684,862
No Same Sex Partners						
Uber Available	0.012*	0.006	0.464*	516.489*	-0.006	0.023***
	(0.006)	(0.006)	(0.251)	(262.401)	(0.006)	(0.008)
Observations	955,014	955,014	955,014	955,014	955,014	955,014
Only UberX Starts						
Uber Available	0.020***	0.017**	0.679**	1966.955***	-0.025***	0.033***
	(0.007)	(0.007)	(0.330)	(389.679)	(0.008)	(0.011)
Observations	395,742	395,742	395,742	395,742	395,742	395,742

Note: Data are from the American Community Survey, restricted to individuals age 22-54. Standard errors are clustered at the CBSA-level. All models use equation (1) and include fixed effects for CBSA and year, interacted with sub-experiment cohort. Employed is a binary variable = 1 if an individual is employed, labor force is a binary variable = 1 if an individual is in the labor force, usual hours worked are equal to the usual hours an individual works per week, wages are equal to annual income from wages, public assist is a binary variable =1 if a person receives any income from public assistance, and married is a binary variable = 1 if the individual is married. The first panel only includes observations in states that ever expanded medicaid, the second panel drops all observations who reported being in a same sex marriage or living with a same sex partner. The final panel restricts the data to only the 2012 through 2014 cohorts (data years 2006-2016) to focus on the effect of UberX launch. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Supplemental Appendix for "Driving Inclusion: The Effect of Improved Transportation for People with Disabilities"

A Definitions of Disability

The American Community Survey asks a series of questions in order to elicit disability status. Broadly, the questions are related to non-temporary cognitive, ambulatory, independent living, self-care, and vision or hearing difficulties. The questions used in the ACS are provided below:

- **Cognitive**: Because of a physical, mental, or emotional condition, does this person have serious difficulty concentrating, remembering, or making decisions?
- **Ambulatory**: Does this person have serious difficulty walking or climbing stairs?
- **Independent Living**: Because of a physical, mental, or emotional condition, does this person have difficulty doing errands alone such as visiting a doctor's office or shopping?
- **Self Care**: Does this person have difficulty dressing or bathing?
- **Vision or Hearing**: Is this person deaf or does he/she have serious difficulty hearing? Is this person blind or does he/she have serious difficulty seeing even when wearing glasses?

B Effects for People without Disabilities

While this paper is focused on the impact of improved access to transportation for people with disabilities, there is also a question about the effects on a broader swath of the population – prime age people without disabilities. There is existing work that explores the labor market effects of Uber's availability using city-level data, by Li, Hong, and Zhang (2018) and Khreis (2019), but this paper includes several outcomes that are not in the prior literature such as marriage rates and public assistance. While people without disabilities have a variety of other transportation options potentially available to them (including taxis, traditional public transportation, and personal vehicles) on-demand transportation services could still impact economic and social outcomes for people without disabilities, however I would anticipate the effects would be much smaller.

There are a number of reasons why the availability of Uber could impact outcomes for non-disabled adults. The first is that car ownership is not uniform across all non-disabled adults. According to the 2019 ACS, approximately 3.5% of non-disabled 22-54 year old white individuals live in a household without a vehicle, compared to 9% of non-white individuals. Similar, albeit smaller, patterns hold for individuals with and without college degrees, with 4.5% of people with college degrees living in households without a vehicle versus 5.5% for non-college degree holders. Uber's availability has the potential to expand access for any group that may not have reliable access to personal vehicles. Even for people with access to a car, new evidence from Barr et al. (2025) reveals that modest car crashes that lead to a temporary loss of access to a personal vehicle can have negative effects on employment among low-income individuals.

In terms of social outcomes, the mechanisms here could operate similarly to those for adults with disabilities. Uber provides increased access to people and places and if it leads to reductions in household stress due to expanded opportunity, it could lead to more persistent marriages. It is also clear from the existing literature that Uber's availability increases binge drinking behavior, with some of that behavior taking place at bars (Teltser, Lennon, and Burgdorf 2021). This implies an increase in social behaviors which could lead to improvements in social outcomes.

Similar to the main analysis of this paper, in this appendix I first use a stacked difference-in-difference design and provide event study evidence to show the effects on people without disabilities. The effects of Uber's availability on outcomes for non-disabled prime age adults can be seen in Figure B1. Panels (a) and (b) confirm the findings of the prior literature, that access to ridesharing services did slightly increase employment and labor force participation for people without disabilities. When compared to the magnitudes in Figure 1 for people with disabilities, the magnitudes here are small. I also observe slight decreases in public assistance receipt (Panel e), as well as increases in wages (Panel d), although for both outcomes there

is visual evidence that might make one wary of violations of the pre-trends assumption. Finally, Panel f shows that there is also a statistically significant increase in marriage rates for people without disabilities.

The overall pattern of results for people without disabilities is quite similar to the main results for people with disabilities – but is Uber a rising tide that lifts all ships equally, or is it doing something more for people with disabilities? To answer this question I move to a stacked triple difference-in-difference specification, which allows me to identify the relative effect of Uber's availability for people with disabilities compared to those without. The main specification is as follows:

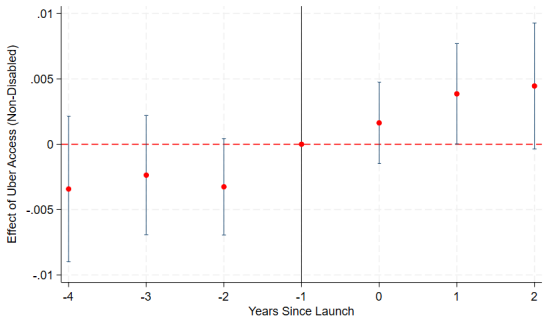
$$\begin{aligned} Y_{icts} = &\alpha_{cs} + \gamma_{ts} + \sum_{\substack{e=-4 \\ e\neq -1}}^{2} \beta_e \left(\mathbf{1}[e_{cts} = e] \times \text{Treat}_{cs}\right) \\ &+ \sum_{\substack{e=-4 \\ e\neq -1}}^{2} \mu_e \left(\mathbf{1}[e_{cts} = e] \times \text{Disabled}_i\right) + \pi \left(\text{Treat}_{cs} \times \text{Disabled}_i\right) \\ &+ \sum_{\substack{e=-4 \\ e\neq -1}}^{2} \delta_e \left(\mathbf{1}[e_{cts} = e] \times \text{Treat}_{cs} \times \text{Disabled}_i\right) \\ &+ \lambda \, \text{Disabled}_i + \epsilon_{icts} \end{aligned} \tag{2}$$

where Y_{icts} is the outcome for individual i in CBSA c at year t in sub-experiment s, α_{cs} are CBSA $\times$ sub-experiment fixed effects, and γ_{ts} are year $\times$ sub-experiment fixed effects. Treat_{cs} is an indicator equal to one if CBSA c is a treated unit in sub-experiment s, e_{cts} denotes event time with $e = -1$ serving as the omitted reference period, and Disabled_i is an indicator equal to one if individual i has any disability. The β_e coefficients capture the dynamic treatment effects for non-disabled individuals, while the δ_e coefficients capture the *differential* effect for disabled individuals relative to non-disabled individuals at each point in the event window. The triple-difference coefficients of interest are therefore the δ_e, with the summary measure reported in tables defined as $\hat{\delta} = \frac{1}{3}\sum_{e=0}^{2} \hat{\delta}_e$. Standard errors are clustered at the CBSA level and all models are estimated using weighted least squares as described above.

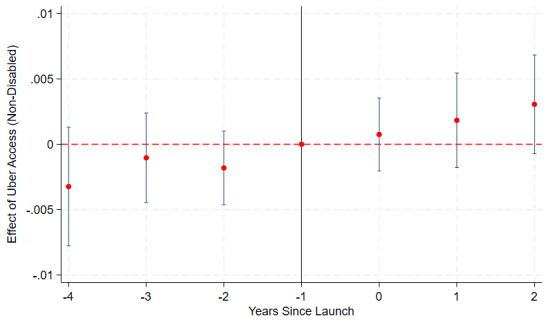
The triple difference results, shown in Table B1, reveal that Uber's availability did have larger effects for people with disabilities across all of the main outcomes, though this is often just shy of statistical significance. This suggests that while improved transportation access has meaningful economic and social effects across the entire population, these effects are stronger among a vulnerable group with potentially fewer alternative transportation options.

To probe the pattern of results for non-disabled adults further, I have also provided heterogeneity analysis by race and educational attainment with the hypothesis that the groups listed above with less access to a personal vehicle (non-white and people without college degrees) would likely see the largest effects. In table B2, I find that is true. The employment effects among non-disabled adults are concentrated among non-white individuals and individuals without a college degree, while the social impacts of Uber's availability are more widespread.

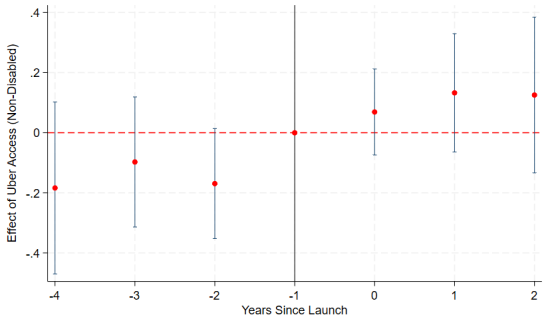
Figure B1: Event Studies - Main Outcomes for People without Disabilities



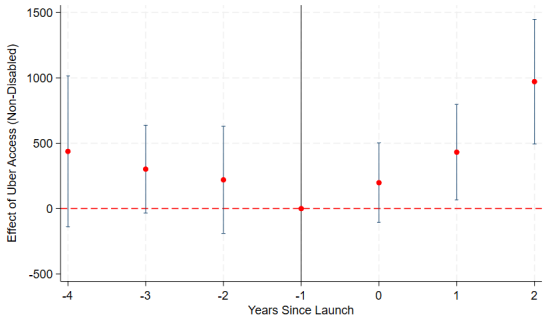
(a) Employment



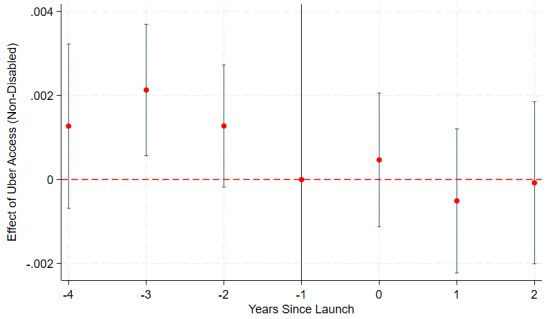
(b) Labor Force Participation



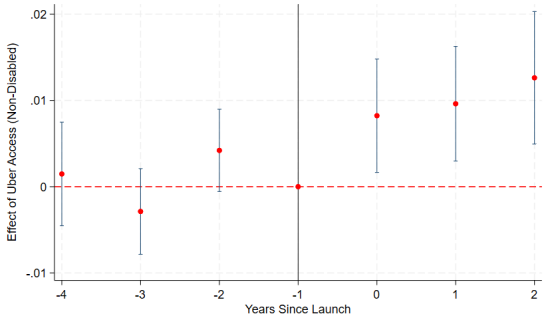
(c) Usual Hours Worked



(d) Wages



(e) Public Assistance



(f) Married

Note: Data are from the American Community Survey. Standard errors are clustered at the CBSA-level. All models include fixed effects for CBSA and year, interacted by sub-experiment cohort. Figures presents coefficients and 95% confidence intervals from Equation (2). Coefficients in all time periods are relative to the year prior to launch where time = 0 is the year of Uber's launch in the treatment group. Employed is a binary variable = 1 if an individual is employed, labor force participation is a binary variable = 1 if an individual is in the labor force, usual hours worked are equal to the usual hours an individual works per week, wages are equal to annual income from wages, public assist is a binary variable =1 if a person receives any income from public assistance, and married is a binary variable = 1 if the individual is married.

Table B1: Triple Difference-in-Difference

	(1) Employed	(2) Labor Force	(3) Public Assistance	(4) Married
Uber Available	0.003*	0.002	-0.000	0.010***
	(0.002)	(0.002)	(0.001)	(0.003)
Uber Available*Disability	0.010	0.004	-0.007	0.012
	(0.006)	(0.006)	(0.005)	(0.008)
Observations	11,875,781	11,875,781	11,875,781	11,875,781

Note: Data are from the American Community Survey. Sample restricted to individuals age 22-54. Standard errors are clustered at the CBSA-level. All models use equation (2) and include fixed effects for CBSA and year, interacted by sub-experiment cohort. Coefficients for all other interactions are excluded from this table in the interest of space. Employed is a binary variable = 1 if an individual is employed, labor force is a binary variable = 1 if an individual is in the labor force, public assistance is a binary variable =1 if a person receives any income from public assistance, and married is a binary variable = 1 if the individual is married. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B2: Non-disabled Effects by Subgroup

	(1)	(2)	(3)	(4)
	Employed	LabForce	Public Assistance	Married
Uber Available	0.000	0.000	0.000	0.008**
	(0.002)	(0.002)	(0.001)	(0.003)
Observations	8,234,658	8,234,658	8,234,658	8,234,658
Control Mean†	0.685	0.744	0.035	0.539
Non-white				
Uber Available	0.009**	0.006**	0.002	0.012***
	(0.004)	(0.003)	(0.002)	(0.004)
Observations	2,677,629	2,677,629	2,677,629	2,677,629
Control Mean†	0.609	0.703	0.067	0.387
No College Degree				
Uber Available	0.006**	0.003*	-0.000	0.012***
	(0.002)	(0.002)	(0.001)	(0.003)
Observations	7,102,244	7,102,244	7,102,244	7,102,244
Control Mean†	0.630	0.706	0.050	0.466
College Degree				
Uber Available	-0.001	-0.001	0.000	0.006
	(0.002)	(0.002)	(0.001)	(0.005)
Observations	3,810,043	3,810,043	3,810,043	3,810,043
Control Mean†	0.807	0.839	0.010	0.657

Note: Data are from the American Community Survey. Sample restricted to individuals age 22-54. Standard errors are clustered at the CBSA-level. All models use equation (1) and include fixed effects for CBSA and year, interacted by sub-experiment cohort. Coefficients for all other interactions are excluded from this table in the interest of space. Employed is a binary variable = 1 if an individual is employed, labor force is a binary variable = 1 if an individual is in the labor force, public assistance is a binary variable =1 if a person receives any income from public assistance, and married is a binary variable = 1 if the individual is married. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

C UberWAV

Through personal correspondence with Uber researchers, I obtained start dates for UberWAV across the twelve cities it has operated in, shown in Table C1. Discussions with the research team revealed that the UberWAV service has had various issues with operating consistency and availability in its operating cities - so a long run analysis of the effects of UberWAV would be inappropriate. Instead, I focus on the impacts of UberWAV in the first cohort of cities to obtain the service in 2014.

For this analysis, I use individuals from Chicago, NYC, Philadelphia, LA, and San Francisco as my treated units and individuals in cities that launched UberWAV *after* my event window as control cities. My first analysis is a simple 2x2 difference-in-difference design, using 2013 as a pre-period and 2014 as a post-period. I conduct my analysis using a two-way fixed effects specification:

$$Y_{ict} = \alpha_c + \gamma_t + \beta UberWAVAvailable_{ct} + \epsilon_{ict} \tag{3}$$

where Y_{ict} represents outcomes for individual i in CBSA c at time t, α_c are CBSA fixed effects, γ_t are year fixed effects, and the standard errors are clustered at the CBSA level. For this part of the analysis, I focus on variables that seemed to be the most impacted by Uber's standard offerings: employment, labor force participation, public assistance, and marriage.

As noted in the main text, UberWAV access did not significantly impact outcomes across the full sample of prime age individuals with disabilities. Importantly, UberWAV launched *after* more general forms of Uber in each city and it may be that the people who would have been induced into behavioral changes already made those changes when UberX or UberBlack became available. It may also be true that UberWAV impacts other outcomes (such as healthcare use or subjective well-being) that are not observed in the American Community Survey, or that UberWAV has impacts beyond my primary sample of 22-54 year olds with any reported disability.

In Table C3 I explore the effects among other age groups, similar to Table D2. While statistically imprecise, there are increases in employment among the younger and older cohorts of disabled individuals, indeed UberWAV does lead to a large increase in labor force participation among young adults, of 4.1 percentage points or a nearly 12% increase over the baseline control average. Among older adults, the labor force impacts are quite noisy, but there are small increases in marriage rates - providing further support for the increased access to people and places mechanism.

To probe further, Table C4 looks at the effects of UberWAV by disability type, noting that these categories are non-exclusive and individuals may report more than one type of limitation. Among individuals with vision or hearing disabilities, I find positive effects on

employment and labor force participation, consistent with the main results and potentially reflecting the advantages of an app-based interface that reduces reliance on phone-based coordination. For individuals with cognitive disabilities or self-care limitations, I find no significant effects, which is consistent with the broader pattern that transportation access alone may be insufficient to overcome the other barriers these groups face.

The estimates for individuals with mobility disabilities are negative for employment and marriage, though these results - and all of the UberWAV results - should be interpreted with considerable caution. The analysis relies on a single pre-period and post-period, the sample is small, and UberWAV's operational consistency has been limited in several cities. Several mechanisms could potentially explain this pattern including service quality concerns, compositional differences among newly-served individuals, or interactions with existing accessible transit infrastructure, but the data do not allow me to distinguish among them. Understanding how individuals with mobility disabilities interact with on-demand accessible transportation remains an important direction for future work.

Table C1: UberWAV Start Dates

City Name	**UberWAV Start Date**
Chicago	March 2014
New York City	August 2014
Philadelphia	September 2014
Los Angeles	November 2014
San Francisco	November 2014
Austin	July 2015
Boston	September 2015
Phoenix	October 2015
Portland	November 2015
Washington DC	December 2015
Houston	April 2016
Salt Lake City	May 2016

Note: Start date data obtained via personal correspondence with Uber researchers.

Table C2: UberWAV Results

	(1)	(2)	(3)	(4)
	Employed	Labor Force	Public Assistance	Married
UberWAV Available	0.002	-0.003	-0.005	-0.002
	(0.010)	(0.005)	(0.006)	(0.009)
Observations	132,153	132,153	132,153	132,153
Control Mean†	0.317	0.391	0.213	0.377
CBSA and Year FE	Yes	Yes	Yes	Yes

Note: Data are from the American Community Survey, 2013-2014. Sample restricted to individuals age 22-54 who reported having any disability. Standard errors are clustered at the CBSA-level. All models use equation (3) and include fixed effects for CBSA and year. Employed is a binary variable = 1 if an individual is employed, labor force is a binary variable = 1 if an individual is in the labor force, public assistance is a binary variable =1 if a person receives any income from public assistance, and married is a binary variable = 1 if the individual is married. †The control mean reports the mean of each outcome in the pre-period years for the control observations in each cohort. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table C3: UberWAV Results by Age Group

	(1) Employed	(2) Labor Force	(3) Public Assistance	(4) Married
Prime Age (22-54)				
UberWAV Available	0.002	-0.003	-0.005	-0.002
	(0.010)	(0.005)	(0.006)	(0.009)
Observations	132,153	132,153	132,153	132,153
Control Mean†	0.373	0.464	0.241	0.340
Young Adult (16-21)				
UberWAV Available	0.044	0.041**	-0.040	-0.005
	(0.033)	(0.019)	(0.034)	(0.006)
Observations	18,746	18,746	18,746	18,746
Control Mean†	0.214	0.348	0.191	0.023
Older Adult (55-67)				
UberWAV Available	0.014	0.012	-0.017**	0.011*
	(0.012)	(0.010)	(0.009)	(0.006)
Observations	120,718	120,718	120,718	120,718
Control Mean†	0.262	0.300	0.180	0.489

Note: Data are from the American Community Survey, 2013-2014. Sample restricted to individuals who reported having any disability. Standard errors are clustered at the CBSA-level. All models use equation (3) and include fixed effects for CBSA and year. Employed is a binary variable = 1 if an individual is employed, labor force is a binary variable = 1 if an individual is in the labor force, public assistance is a binary variable =1 if a person receives any income from public assistance, and married is a binary variable = 1 if the individual is married. †The control mean reports the mean of each outcome in the pre-period years for the control observations in each cohort. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

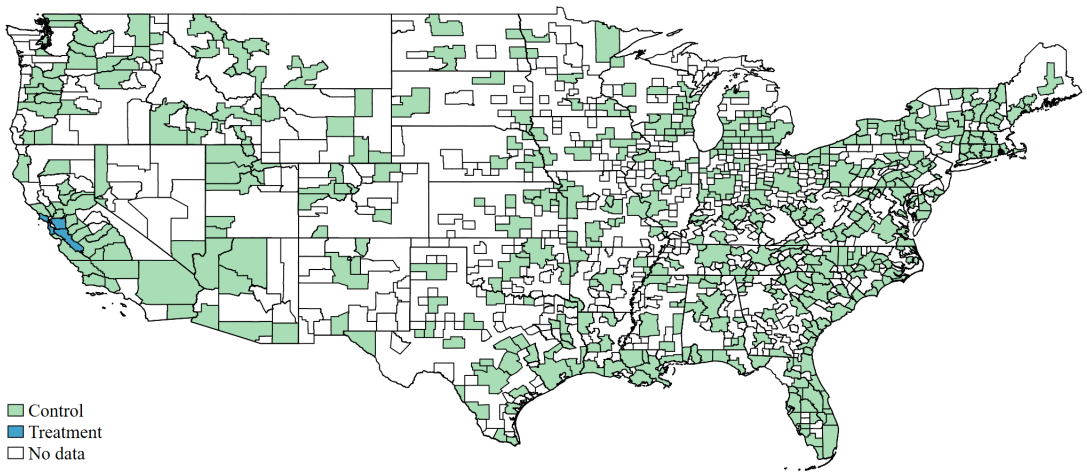
Table C4: UberWAV Results by Disability Type

	(1) Employed	(2) Labor Force	(3) Public Assistance	(4) Married
Vision/Hearing				
UberWAV Available	0.032*	0.023**	-0.004	0.009
	(0.017)	(0.010)	(0.013)	(0.013)
Observations	42,629	42,629	42,629	42,629
Control Mean†	0.517	0.605	0.171	0.407
Mobility				
UberWAV Available	-0.029***	-0.036***	0.011	-0.035**
	(0.006)	(0.009)	(0.015)	(0.015)
Observations	55,865	55,865	55,865	55,865
Control Mean†	0.271	0.349	0.273	0.359
Self Care				
UberWAV Available	-0.001	0.001	-0.002	-0.006
	(0.011)	(0.010)	(0.010)	(0.015)
Observations	54,563	54,563	54,563	54,563
Control Mean†	0.202	0.267	0.352	0.288
Cognitive				
UberWAV Available	0.007	0.004	-0.021*	-0.004
	(0.007)	(0.013)	(0.012)	(0.008)
Observations	64,705	64,705	64,705	64,705
Control Mean†	0.265	0.362	0.320	0.240

Note: Data are from the American Community Survey, 2013-2014. Sample restricted to individuals age 22-54 who reported having a disability. Standard errors are clustered at the CBSA-level. All models use equation (3) and include fixed effects for CBSA and year. Employed is a binary variable = 1 if an individual is employed, labor force is a binary variable = 1 if an individual is in the labor force, public assistance is a binary variable =1 if a person receives any income from public assistance, and married is a binary variable = 1 if the individual is married. †The control mean reports the mean of each outcome in the pre-period years for the control observations in each cohort. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

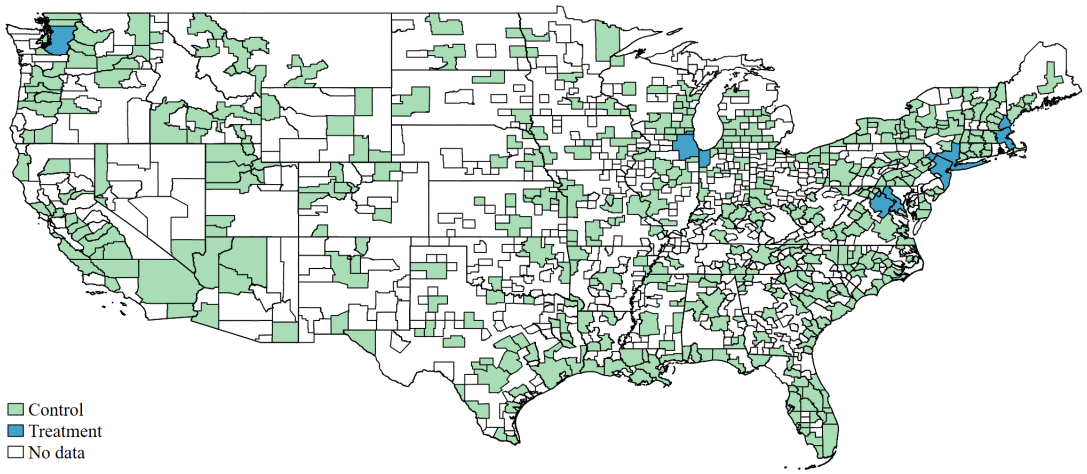
D Supplemental Tables and Figures

Figure D1: 2010 Cohort Treatment Variation



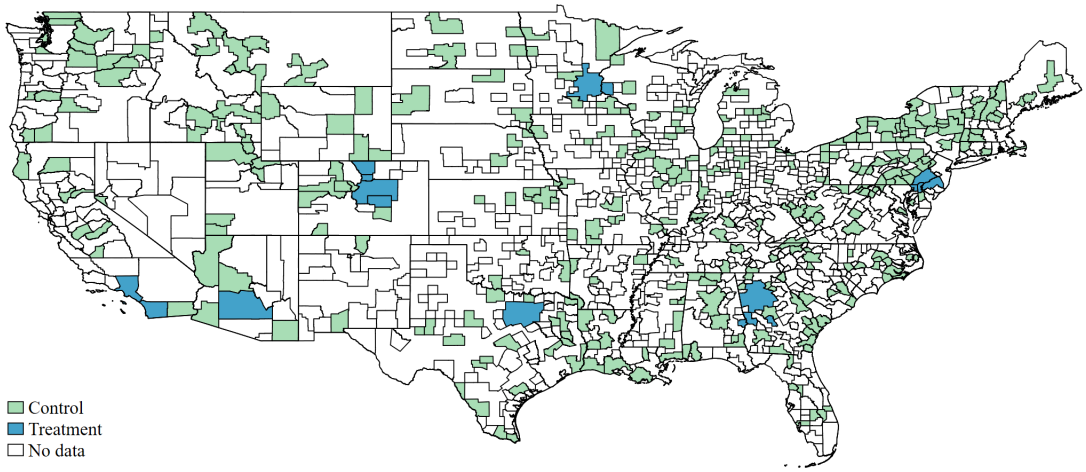
Note: Start date data are from Hall, Palsson, and Price (2018) and personal correspondence with Uber. Map shows the cities that were treated in 2010 and the cities that are used in the control group for that cohort (who received Uber in 2013 or later).

Figure D2: 2011 Cohort Treatment Variation



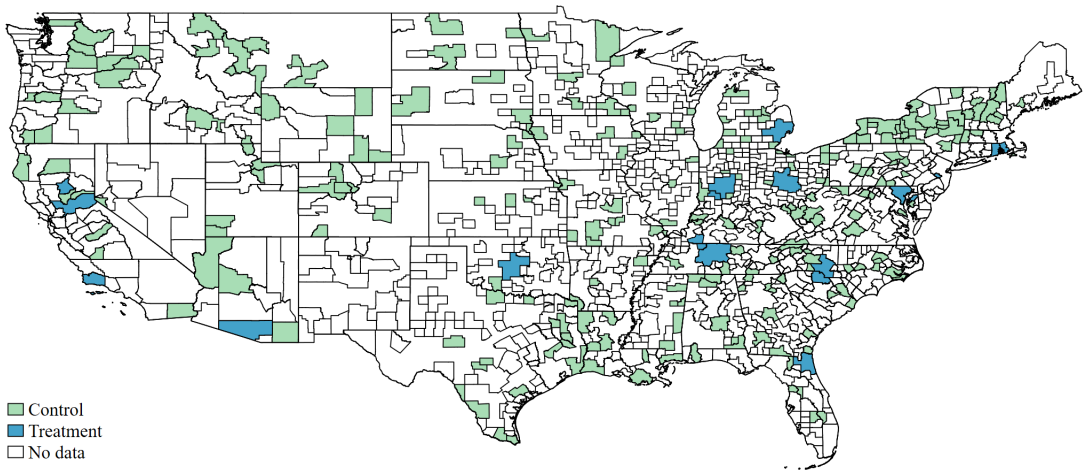
Note: Start date data are from Hall, Palsson, and Price (2018) and personal correspondence with Uber. Map shows the cities that were treated in 2011 and the cities that are used in the control group for that cohort (who received Uber in 2014 or later).

Figure D3: 2012 Cohort Treatment Variation



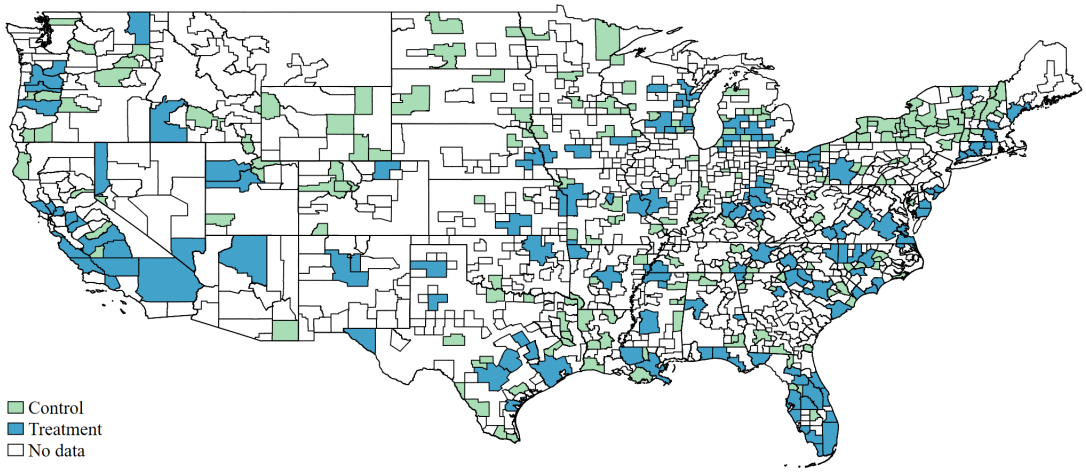
Note: Start date data are from Hall, Palsson, and Price (2018) and personal correspondence with Uber. Map shows the cities that were treated in 2012 and the cities that are used in the control group for that cohort (who received Uber in 2015 or later).

Figure D4: 2013 Cohort Treatment Variation



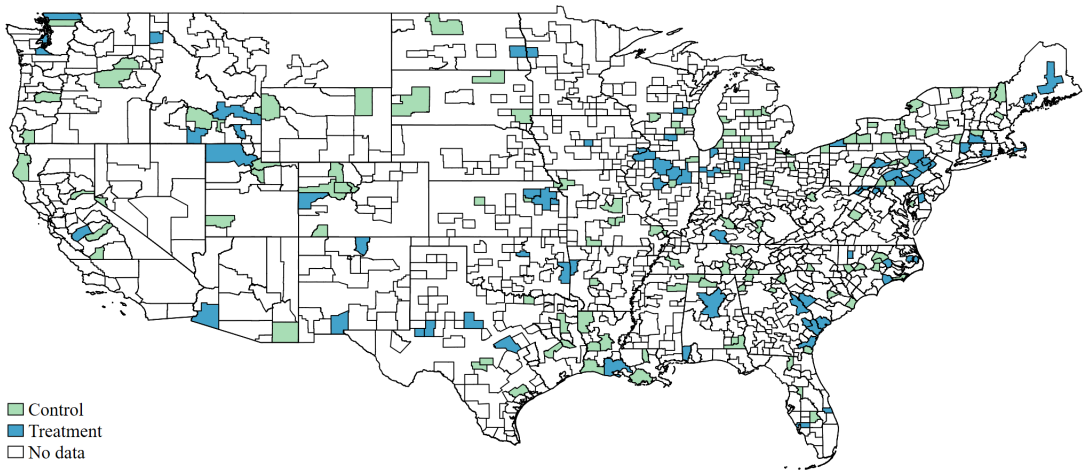
Note: Start date data are from Hall, Palsson, and Price (2018) and personal correspondence with Uber. Map shows the cities that were treated in 2013 and the cities that are used in the control group for that cohort (who received Uber in 2016 or later).

Figure D5: 2014 Cohort Treatment Variation



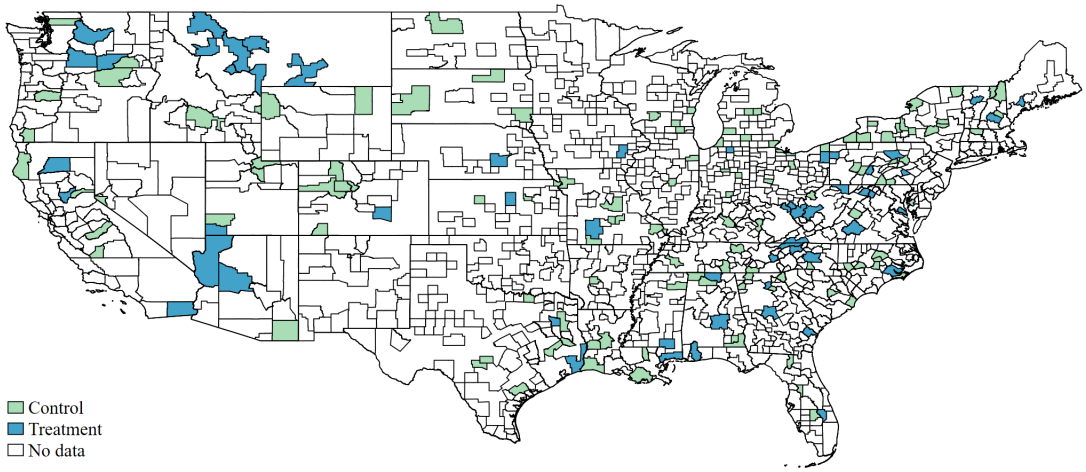
Note: Start date data are from Hall, Palsson, and Price (2018) and personal correspondence with Uber. Map shows the cities that were treated in 2014 and the cities that are used in the control group for that cohort (who received Uber in 2017 or later).

Figure D6: 2015 Cohort Treatment Variation



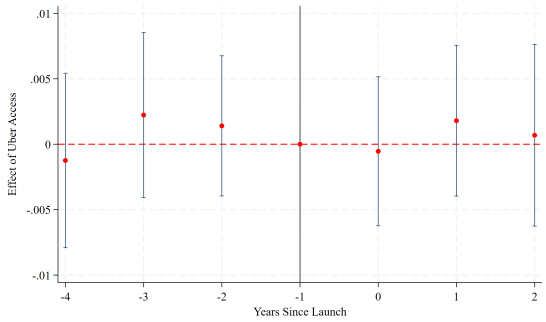
Note: Start date data are from Hall, Palsson, and Price (2018) and personal correspondence with Uber. Map shows the cities that were treated in 2015 and the cities that are used in the control group for that cohort (who received Uber in 2018 or later).

Figure D7: 2016 Cohort Treatment Variation

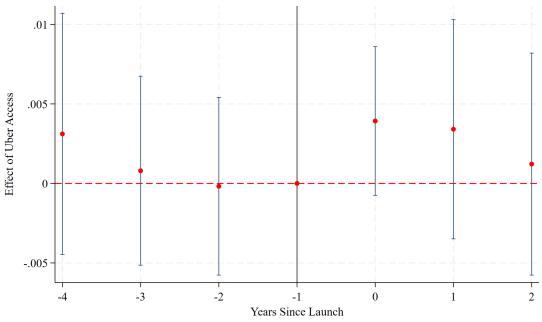


Note: Start date data are from Hall, Palsson, and Price (2018) and personal correspondence with Uber. Map shows the cities that were treated in 2016 and the cities that are used in the control group for that cohort (who received Uber in 2019 or later).

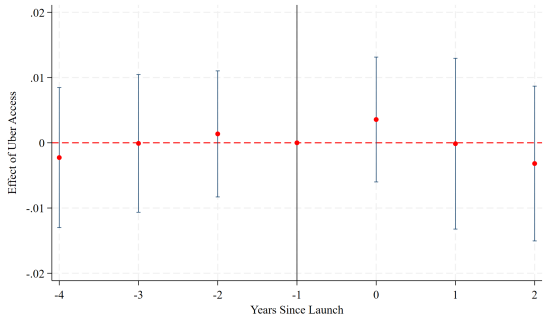
Figure D8: Event Studies - Supplemental Employment and Income Outcomes



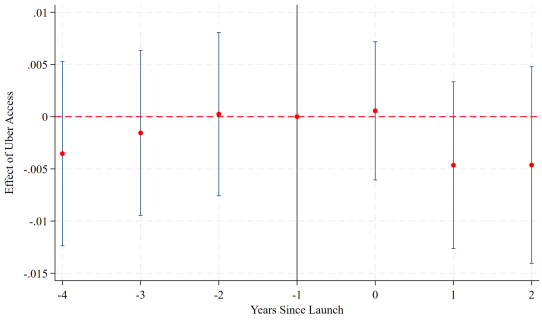
(a) Transportation Occupations



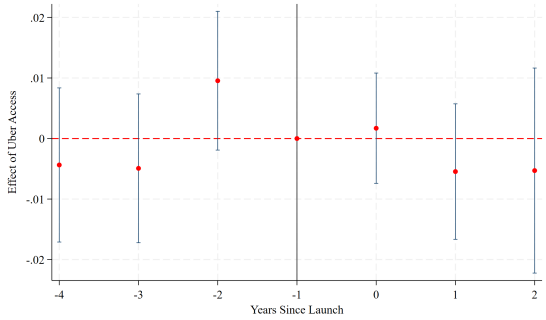
(b) Self Employment



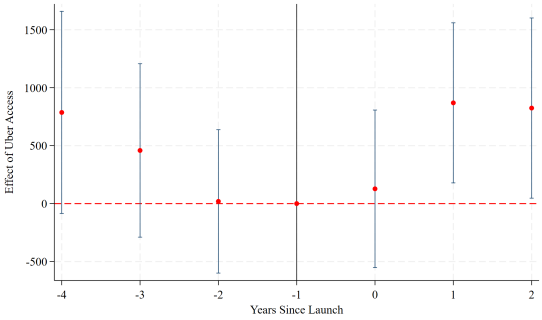
(c) Social Security



(d) Welfare



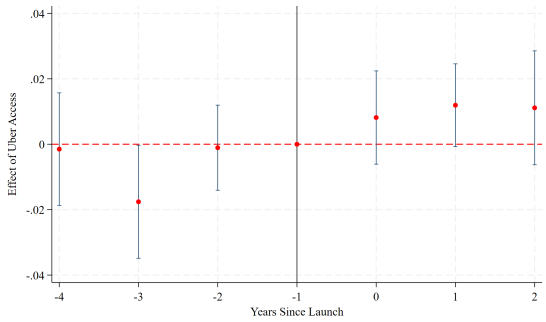
(e) SSI



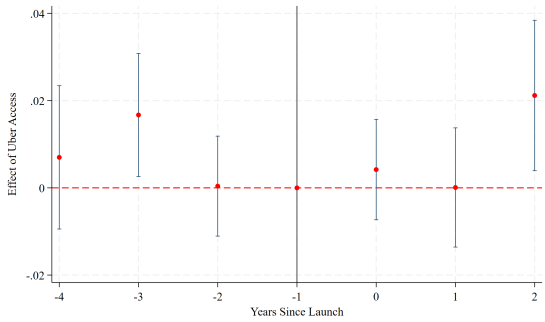
(f) Total Income

Note: Data are from the American Community Survey, restricted to individuals who report having a disability. Standard errors are clustered at the CBSA-level. All models include fixed effects for CBSA and year, interacted with sub-experiment cohort. Figures presents coefficients and 95% confidence intervals from Equation (1). Coefficients in all time periods are relative to the year prior to launch where time = 0 is the year of Uber's launch in the treatment group. Transportation Occupation is a binary variable = 1 if an individual is employed in a transportation-related occupation, Self Employment is a binary variable = 1 if an individual reports being self-employed, Social Security is a binary variable = 1 if an individual receives any income from social security, Welfare is a binary variable = 1 if an individual receives any income from welfare, SSI is a binary variable = 1 if an individual receives any income from supplemental social security, Total Income are equal to the annual total personal income.

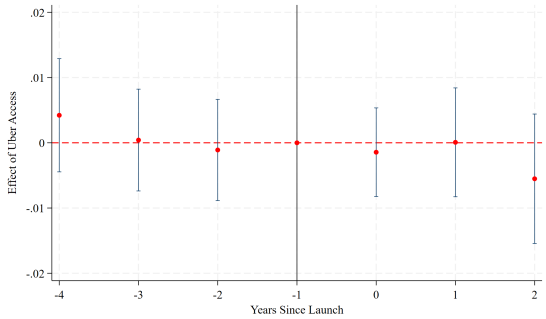
Figure D9: Event Studies - Supplemental Household Composition Outcomes



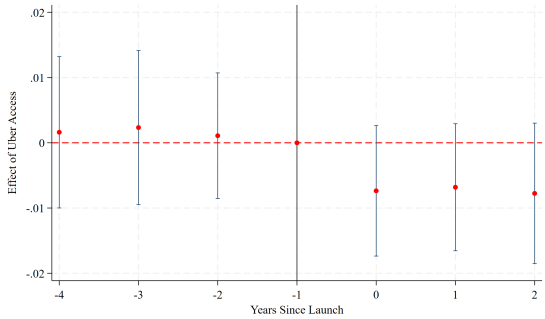
(a) Living in a Household with Kids



(b) Living with Parents



(c) Living with Unmarried Partner



(d) Divorce

Note: Data are from the American Community Survey, restricted to individuals who report having a disability. Standard errors are clustered at the CBSA-level. All models include fixed effects for CBSA and year, interacted with sub-experiment cohort. Figures presents coefficients and 95% confidence intervals from an event study specification. Coefficients in all time periods are relative to the year prior to launch where time = 0 is the year of Uber's launch in the treatment group. Living in a Household with Kids is a binary variable = 1 if an individual lives in a household with children, Living with Parents is a binary variable = 1 if the individual reports living in a household with their parents, Living with Unmarried Partner is a binary variable = 1 if an individual reports living in a household with their unmarried partner, Divorce = 1 if an individual reports being divorced.

Table D1: Usual Transportation to Work by Disability Status

	Any Disability	No Disability
Own Vehicle	0.727	0.845
	(0.446)	(0.362)
Bus	0.048	0.025
	(0.213)	(0.158)
Train or Subway	0.015	0.028
	(0.120)	(0.165)
Specialized Bus or Van	0.030	0.001
	(0.172)	(0.031)
Passenger in Someone Else's Car	0.062	0.023
	(0.241)	(0.149)
Carpool	0.017	0.017
	(0.128)	(0.129)
Taxi	0.003	0.002
	(0.058)	(0.040)
Bike	0.014	0.007
	(0.116)	(0.086)
Walking	0.039	0.022
	(0.193)	(0.148)
Other	0.030	0.018
	(0.171)	(0.133)
Work from Home	0.037	0.032
	(0.188)	(0.177)
Observations	977	36,562

Note: Data are from the 2012 Current Population Survey Disability Supplement and are at the individual-level. The sample is restricted to individuals age 22 to 54 who are employed. Values represent the usual means of transportation to work by disability status in 2012. Standard deviations in parentheses.

Table D2: Main Results - Age Heterogeneity

	(1) Employed	(2) Labor Force	(3) Usual Hours	(4) Wages	(5) Public Assistance	(6) Married
Prime Age (22-54)						
Uber Available	0.012*	0.006	0.480*	575.962**	-0.007	0.023***
	(0.006)	(0.006)	(0.251)	(261.038)	(0.005)	(0.008)
Observations	963,494	963,494	963,494	963,494	963,494	963,494
Control Mean†	0.390	0.475	14.723	11,965.925	0.245	0.385
Young Adult (16-21)						
Uber Available	-0.006	0.013	-0.061	-170.897	0.002	0.001
	(0.016)	(0.016)	(0.500)	(245.086)	(0.013)	(0.005)
Observations	120,436	120,436	120,436	120,436	120,436	120,436
Control Mean†	0.227	0.383	5.981	2,288.535	0.186	0.031
Older Adult (55-67)						
Uber Available	0.006	0.006	0.243	166.111	-0.001	0.009
	(0.005)	(0.006)	(0.228)	(458.890)	(0.006)	(0.006)
Observations	870,743	870,743	870,743	870,743	870,743	870,743
Control Mean†	0.267	0.298	9.869	9,699.336	0.176	0.537

Note: Table uses individual-level data from the 2006-2019 American Community Survey. Sample restricted to individuals age 16-67 who reported having any disability. Standard errors are clustered at the CBSA-level. All models use equation (1) and include fixed effects for CBSA and year, interacted with sub-experiment cohort. Employed is a binary variable = 1 if an individual is employed, labor force is a binary variable = 1 if an individual is in the labor force, usual hours worked are equal to the usual hours an individual works per week, wages are equal to annual income from wages, public assist is a binary variable =1 if a person receives any income from public assistance, and married is a binary variable = 1 if the individual is married. †The control mean reports the mean of each outcome in the pre-period years for the control observations in each cohort. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table D3: Main Results - Race and Gender Heterogeneity

	(1) Employed	(2) Labor Force	(3) Usual Hours	(4) Wages	(5) Public Assistance	(6) Married
White						
Uber Available	0.009	0.004	0.480	713.624**	-0.009	0.031***
	(0.007)	(0.007)	(0.294)	(346.656)	(0.006)	(0.009)
Observations	688,945	688,945	688,945	688,945	688,945	688,945
Control Mean†	0.345	0.410	12.849	11,370.379	0.194	0.456
Non-white						
Uber Available	0.019*	0.011	0.495	367.254	-0.001	-0.003
	(0.011)	(0.011)	(0.448)	(379.704)	(0.013)	(0.012)
Observations	274,547	274,547	274,547	274,547	274,547	274,547
Control Mean†	0.279	0.358	10.027	7,209.376	0.282	0.311
Male						
Uber Available	0.018*	0.012	0.741*	1116.733**	-0.008	0.021**
	(0.010)	(0.009)	(0.433)	(455.233)	(0.007)	(0.010)
Observations	460,153	460,153	460,153	460,153	460,153	460,153
Control Mean†	0.353	0.432	13.872	13,061.446	0.191	0.445
Female						
Uber Available	0.005	-0.002	0.180	-20.973	-0.005	0.026***
	(0.009)	(0.010)	(0.319)	(359.429)	(0.009)	(0.009)
Observations	503,341	503,341	503,341	503,341	503,341	503,341
Control Mean†	0.307	0.365	10.547	7,796.723	0.237	0.399

Note: Table uses individual-level data from the 2006-2019 American Community Survey. Sample restricted to individuals age 22-54 who reported having any disability. Standard errors are clustered at the CBSA-level. All models use equation (1) and include fixed effects for CBSA and year, interacted with sub-experiment cohort. Employed is a binary variable = 1 if an individual is employed, labor force is a binary variable = 1 if an individual is in the labor force, usual hours worked are equal to the usual hours an individual works per week, wages are equal to annual income from wages, public assist is a binary variable =1 if a person receives any income from public assistance, and married is a binary variable = 1 if the individual is married. †The control mean reports the mean of each outcome in the pre-period years for the control observations in each cohort. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table D4: Main Results - Educational Attainment Heterogeneity

	(1) Employed	(2) Labor Force	(3) Usual Hours	(4) Wages	(5) Public Assistance	(6) Married
No College Degree						
Uber Available	0.011*	0.005	0.445	334.581	-0.007	0.025***
	(0.007)	(0.006)	(0.278)	(264.961)	(0.006)	(0.009)
Observations	835,203	835,203	835,203	835,203	835,203	835,203
Control Mean†	0.308	0.379	11.193	8,455.558	0.229	0.407
College Degree						
Uber Available	0.007	0.000	0.477	731.246	-0.002	0.009
	(0.015)	(0.015)	(0.736)	1624.703)	(0.010)	(0.017)
Observations	128,289	128,289	128,289	128,289	128,289	128,289
Control Mean†	0.511	0.559	20.478	26,505.480	0.090	0.548

Note: Table uses individual-level data from the 2006-2019 American Community Survey. Sample restricted to individuals age 22-54 who reported having any disability. Standard errors are clustered at the CBSA-level. All models use equation (1) and include fixed effects for CBSA and year, interacted with sub-experiment cohort. Coefficients for $Uber_{cs}$ and $Post_{ts}$ are excluded from these tables in the interest of space. Employed is a binary variable = 1 if an individual is employed, labor force is a binary variable = 1 if an individual is in the labor force, usual hours worked are equal to the usual hours an individual works per week, wages are equal to annual income from wages, public assist is a binary variable =1 if a person receives any income from public assistance, and married is a binary variable = 1 if the individual is married. †The control mean reports the mean of each outcome in the pre-period years for the control observations in each cohort. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table D5: Main Results - Disability Heterogeneity

	(1) Employed	(2) Labor Force	(3) Usual Hours	(4) Wages	(5) Public Assistance	(6) Married
Vision/Hearing						
Uber Available	0.019*	0.008	0.646	324.633	-0.018*	0.027**
	(0.011)	(0.010)	(0.452)	(610.937)	(0.010)	(0.012)
Observations	300,367	300,367	300,367	300,367	300,367	300,367
Control Mean†	0.435	0.500	16.803	15,026.066	0.157	0.492
Mobility						
Uber Available	0.008	0.008	0.200	462.038	0.004	0.023**
	(0.007)	(0.008)	(0.298)	(357.074)	(0.008)	(0.010)
Observations	454,178	454,178	454,178	454,178	454,178	454,178
Control Mean†	0.239	0.288	8.800	7,559.617	0.240	0.448
Self Care						
Uber Available	-0.008	-0.007	-0.199	-93.795	-0.004	0.021*
	(0.007)	(0.009)	(0.282)	(291.075)	(0.011)	(0.011)
Observations	380,597	380,597	380,597	380,597	380,597	380,597
Control Mean†	0.167	0.214	5.586	4,589.529	0.314	0.370
Cognitive						
Uber Available	0.002	-0.005	0.186	608.005*	-0.010	0.017**
	(0.008)	(0.007)	(0.318)	(311.898)	(0.008)	(0.009)
Observations	433,224	433,224	433,224	433,224	433,224	433,224
Control Mean†	0.236	0.319	7.904	5,768.201	0.304	0.294

Note: Table uses individual-level data from the 2006-2019 American Community Survey. Sample restricted to individuals age 22-54 who reported having any disability. Standard errors are clustered at the CBSA-level. All models use equation (1) and include fixed effects for CBSA and year, interacted with sub-experiment cohort. Employed is a binary variable = 1 if an individual is employed, labor force is a binary variable = 1 if an individual is in the labor force, usual hours worked are equal to the usual hours an individual works per week, wages are equal to annual income from wages, public assist is a binary variable =1 if a person receives any income from public assistance, and married is a binary variable = 1 if the individual is married. †The control mean reports the mean of each outcome in the pre-period years for the control observations in each cohort. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table D6: Main Results - Transportation Heterogeneity

	(1) Employed	(2) Labor Force	(3) Usual Hours	(4) Wages	(5) Public Assistance	(6) Married
Worse Local Public Transportation						
Uber Available	0.002	-0.002	0.150	388.090	0.002	0.022*
	(0.010)	(0.010)	(0.411)	(427.575)	(0.008)	(0.012)
Observations	476,423	476,423	476,423	476,423	476,423	476,423
Control Mean†	0.384	0.470	14.549	11,662.694	0.240	0.395
Better Local Public Transportation						
Uber Available	0.016**	0.008	0.649**	-146.238	-0.001	0.008
	(0.007)	(0.009)	(0.299)	(540.429)	(0.008)	(0.009)
Observations	485,618	485,618	485,618	485,618	485,618	485,618
Control Mean†	0.413	0.491	15.321	13,041.029	0.263	0.351

Note: Table uses individual-level data from the 2006-2019 American Community Survey. Sample restricted to individuals age 22-54 who reported having any disability. Standard errors are clustered at the CBSA-level. All models use equation (1) and include fixed effects for CBSA and year, interacted with sub-experiment cohort. Coefficients for $Uber_{cs}$ and $Post_{ts}$ are excluded from these tables in the interest of space. Employed is a binary variable = 1 if an individual is employed, labor force is a binary variable = 1 if an individual is in the labor force, usual hours worked are equal to the usual hours an individual works per week, wages are equal to annual income from wages, public assist is a binary variable =1 if a person receives any income from public assistance, and married is a binary variable = 1 if the individual is married. Transportation quality is measured by the Transit Connectivity Index by the Center for Neighborhood Technology. †The control mean reports the mean of each outcome in the pre-period years for the control observations in each cohort. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table D7: Robustness Check: Predict Timing

	(1) Employed	(2) LabForce	(3) Usual Hours	(4) Wages	(5) Public Assistance	(6) Married	(7) Disability Share
Lagged Employed	0.003						
	(0.010)						
Lagged Labor Force Participation		-0.013					
		(0.012)					
Lagged Usual Hours			0.000				
			(0.000)				
Lagged Wages				-0.000			
				(0.000)			
Lagged Public Assistance					-0.015		
					(0.014)		
Lagged Marriage						0.009	
						(0.013)	
Lagged Disability Share							0.216***
							(0.044)
Observations	191	191	191	191	191	191	191

Note: Data are from the American Community Survey. Standard errors are clustered at the CBSA-level. Analysis is at the CBSA-level, where the outcome variable is the year the CBSA received Uber (their treatment year) and the independent variable in each specification is the average employment rate, labor force participation rate, usual hours worked, income from wages, public assistance receipt, or marriage rate for people with disabilities or disability share of the population in that CBSA in the year prior to getting Uber. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table D8: Robustness Check: Composition

	(1) Any Disability	(2) Any Migration
Uber Available	0.0004	-0.003
	(0.001)	(0.006)
Observations	11,875,781	963,494
Control Mean†	0.092	0.181

Note: Data are from the American Community Survey, restricted to individuals age 22-54. Standard errors are clustered at the CBSA-level. All models use equation (1) and include fixed effects for CBSA and year, interacted with sub-experiment cohort. Column (1) presents results on the proportion of people who have a disability (an indicator variable = 1 if a person responds that they have any disability). Column (2) reports the effects on migration, a binary variable = 1 if a person moved in the last year, for people with disabilities. †The control mean reports the mean of each outcome in the pre-period years for the control observations in each cohort. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$