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

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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, which may serve as "reliability insurance" in case other modes of transit fail. Leveraging the roll-out of Uber, I use a difference-in-differences approach to show that the availability of reliable and flexible transportation leads to improvements in social (increased marriage rates) and economic (increased labor force participation and reduced reliance on public assistance) participation. The reduction in public assistance suggests there may be efficiency gains from government intervention in this setting.

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*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 labor force participation (41% vs 81%), lower average earnings ($25,000 vs $48,000), and higher rates of reliance on social assistance programs (21% vs 2%).[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 (Carol 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 economic and social inclusion (Bezyak et al. 2020; Lindsay 2011; Rintala et al. 1997; Sabella and Bezyak 2019).[2] 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 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 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

[1] Source: 2019 5-Year ACS.

[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, D. Johnson, and Lucas (2020).

[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.

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 ride-sharing 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.

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 adults increases by 1.4 percentage points (a 3.3% increase over baseline), labor force participation increases by 1.1 percentage points (2.1%), public assistance receipt decreases by 1 percentage point (4.5%), and marriage rates increase by 1.7 percentage points (4.3%). For context, the magnitude of the increase in marriage rates is 10% 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 tend to be larger for people with lower quality local public transportation systems. This provides support for the idea that Uber is likely acting as a form of insurance - a fail-safe in case more traditional transit methods won't suffice.

Back of the envelope calculations suggest there may be efficiency gains from government support of reliability insurance. Using both my estimated effects and ride-share ridership statistics for people with disabilities from Federal Highway Administration (2022), I find that the reduction in public assistance could reduce government expenditures by up to $70 million per month. At the same time, I find that the total possible monthly expense on ride-share transportation could be as high as $20 million. This suggests that there are possible efficiency gains to be made from the government subsidizing these types of transportation expenditures, or from encouraging the expansion of these services into other geographies – especially places with low-quality public transportation.

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 (M. K. 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 W. G. Johnson 1994, 2000; Lindsay 2011). I will be the first to consider the understudied role of improved 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 Insurance (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). These benefits serve as a lifeline for many, but the current program in the United States may be associated with unintended consequences for recipients. I contribute to the existing literature on disability insurance 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 (41% vs. 80%), labor force participation rates (50% vs. 86%), and incomes ($21,770 vs. $43,180), 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.

2.2 Transportation for People with Disabilities

Transportation stands out as a major barrier to economic inclusion for disabled people. Of 13 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, Table 2 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

[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.

[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, J. Graham, and M. Jones 2009, Sundar et al. 2018, Hernandez et al. 2007, Meltzer, Robinson, and Fisher 2019, Carolyn Graham et al. 2018, Milfort et al. 2015.

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 (J. L. 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 window 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 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 ride-share, 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 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. Researchers have previously looked at how Uber impacted the taxi industry, public transportation, health behaviors, traffic incidents, local labor markets, and driver-partner well-being (Berger, C. Chen, and Frey 2018; Berger, Frey, et al. 2019; Brazil and Kirk 2016; M. K. Chen et al. 2019; Dills and Mulholland 2018; Greenwood and Wattal 2017; Hall and Krueger 2018; Khreis 2019; Z. Li, Hong, and Zhang 2018; Teltser, Lennon, and Burgdorf 2021). Z. 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. Both

[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.

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.[8] 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 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.

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

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 and Teltser, Lennon, and Burgdorf (2021)'s appendix.[9] The earliest recorded Uber start date is in 2010, and the start date data are complete through 2017. 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. 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.[10] 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.

The primary outcome data come from the Ruggles et al. (2024) Integrated Public Use Microdata (IPUMs) American Community Survey (ACS) spanning 2006 to 2016. 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 400 identified counties in the data. Geographic information is exclusively available for urban places, but as Uber is also primarily available in urban places, this limitation is unlikely to be a concern. 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

[9]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."

[10]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.

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 (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, $10,000, or $20,000) or if they usually work above a certain number of hours each week (5, 20, or 40). For outcomes such 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 6 questions. In my analysis I will consider a person "disabled" if they respond affirmatively to any of the six questions.[11] 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 Y. Li (2019). This method essentially compares cities with early adoption to those with later adoption

[11] 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.

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 years prior to the event and 3 years after. 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.[12] 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, I reduce the possible bias associated with endogenous entry. In the following sections I will provide further evidence to support this.

The main specification follows a simple difference-in-differences design:

$$Y_{icts} = \alpha_c + \gamma_t + \beta_1 Uber_{cs} + \beta_2 Post_{ts} + \beta_3 UberAvailable_{cts} + \epsilon_{ict} \tag{1}$$

where Y_{icts} represents outcomes for individual i in CBSA c at time t in stack s, α_c are CBSA fixed effects, γ_t are year fixed effects, and the standard errors are clustered at the CBSA level.[13] $Uber_{cs}$ is a binary variable equal to one if CBSA c was part of cohort that got Uber in stack s, and zero otherwise. $Post_{ts}$ is a binary variable equal to one if year t in stack s is a year greater than or equal to the launch year. $UberAvailable_{cts}$ is the interaction between $Uber_{cs}$ and $Post_{ts}$, this term is a binary variable that equals one if CBSA c obtains Uber in stack s and the year t is after the launch. The coefficient of interest is β_3 which measures the impact of the availability of flexible and reliable transportation, through Uber.

In the robustness section below I investigate concerns of internal validity in depth. The

[12] Maps documenting the identifying variation for each treatment cohort are presented in Figures D1 through D5.

[13] In a stacked DiD, $Uber_{cs}$ and $Post_{ts}$ are not co-linear with the fixed effects because the same CBSA could be a member of the treated group in one panel and a member of the control group in another stacked panel. Similarly, a year could be a pre-period year in one panel and a post-period year in another.

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).[14] I also show that the overall pattern of results holds with the inclusion of geographic or individual-level controls, CBSA-specific linear time trends, and other alternative specifications.

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.[15] 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 3. Access to improved transportation generates significant increases in labor force engagement, with a 1.4 percentage point (3.3%) increase in employment, driven primarily by increased participation in the labor force (1.1 percentage points or 2.1%). 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 (16 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.

While the estimated effect of improved transportation on wages is positive and similarly

[14] Event study plots for all supplemental outcomes can be found in the Appendix (Figures D6 and D7).

[15] 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 and labor force participation effects of Uber's availability that Z. Li, Hong, and Zhang (2018) and Khreis (2019) find. I also find small effects on public assistance and 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.

sized to the employment effects ($336 or 2.5%), it is too imprecisely estimated to draw strong conclusions. The imprecise 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 3 to Table 4 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 $10,000, and almost no increase in people earning over $20,000 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 3 to Table 4, the observed percentage point increase in employment was the same as the increase in people working at least 5 hours a week, and very close to those working at least 20 hours a week. The effect on people working more than 40 hours a week is close to 1 percentage point (3%). This increase could be due to people who switched from being unemployed or out of the labor force 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 Z. Li, Hong, and Zhang (2018) and Khreis (2019) suggest. In Table 4 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.

This increase in labor force attachment is accompanied by reductions in public assistance receipt among people with disabilities, by 1 percentage point, or a 4.5% reduction from the pre-period baseline. 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 decreases reliance on public assistance as barriers to active labor force engagement are removed. Table 5 shows that nearly all of the decrease in public assistance was driven by reductions in Supplemental Security Income (SSI), which is likely to be expected for this population. This decline in public assistance income is ultimately mostly offset by the imprecise increase in wages, because total incomes do not exhibit any statistically meaningful changes.

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 1.7 percentage points, or 4.3% (Table 3). The observed decline in Supplemental Security Income, which is often tied to strict asset limits that disincentivize marriage, further supports the idea that increased employment may be enabling more disabled individuals to form and maintain partnerships without the fear of losing benefits. Reductions in SSI are unlikely to explain all of the change in marriage, however, as the magnitude of the effect on SSI is around half the size of the effect on marriage. I examine other household composition measures as well - 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. There is a small imprecise negative effect on living with ones parents which may suggest a reduced need for familial care-giving support but this is not conclusive. Overall, either through increased access to social events or through reductions in public assistance which may disincentivize marriage, I find evidence that Uber led to improved social inclusion via marriage.

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 years old) adults, shown in Table 6 as well as Figures 2 and 4. These findings indicate that this age groups, 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 outcomes for young adults (16-21) or older adults (55-67). However, older adults see statistically significant increases in marriage rates, 1.2 percentage points or 2.3%.

The effects on employment and marriage are remarkably consistent across other demographic groups including race, educational attainment, and gender, although some of the effects are imprecise. As seen in Figures 2 and 4 the confidence intervals for all demographic groups overlap.[16] Regardless, I observe slightly larger employment effects for disadvantaged groups. The effects are larger for non-white compared to white individuals, and for people without a college degree compared to people with a college degree.

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).

[16] Details of these results can be found in Appendix Tables D1 and D2

The subgroup analysis by disability type (Table 7 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 (3.4%) in employment and a 3 percentage point (6.7%) 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 with vision/hearing, mobility, and self care limitations but it is important to note that these groups also had higher marriage rates in the pre-period. 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 or public assistance receipt.

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. Overall, the results (Table 8 and Figures 3 and 5) show that almost all of the improvements following Uber's introduction tend to be among people in places with worse local public transportation, which supports the argument that Uber may be used as insurance in case of unreliable local transit.

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.[17]

While the visual evidence suggests that the parallel trends assumption is not violated, I also conduct a version of my analysis that includes CBSA-specific linear time trends. These terms control for confounding factors that lead to potentially differing trends in the outcome variables that are specific to each geography.[18] These results, found in Table 9, show that the qualitative pattern of results are robust to the inclusion of these additional terms. While the effects on public assistance and marriage do not retain their statistical significance in this case, the addition of linear time trends may be over-controlling and thus attenuating these results.

Another test to check for endogenous timing is the inclusion of 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 9, 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, etc) in the year prior to Uber's launch. Table D3 presents these results. On average, places with higher labor force participation rates received access to Uber around 1 year earlier, but there is no consistent sign across these results. Places with higher employment rates, marriage rates and average usual hours worked 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, none of these results are statistically precise. This

[17]Event study figures for the supplemental outcomes can be found in the appendix, Figures D6 and D7.

[18]While this robustness check is often used in the analysis of Uber's impact on various other outcomes, prior work (Wolfers 2006) has shown that it may instead exacerbate biases by over-controlling for time-varying treatment effects.

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.

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 D4. 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 1) 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 both individual- and CBSA-level controls. The specific individual controls include age, as well as indicators for being female, nonwhite, or having a college degree. The CBSA-level 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, in the third panel of Table 9, does not significantly alter the magnitude or statistical significance of the estimates, providing additional confidence in the robustness of the results.

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 early cohorts (2010 and 2011) that were treated during or immediately after the recession. 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 9, confirm that the main effects remain robust even after dropping these early treatment cohorts. Overall, my main findings are robust to a variety of different specification choices.

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.[19] Overall, we see that 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.

4.5 Costs and Benefits

Through back-of-the-envelope calculations I roughly quantify the efficiency gains from improved transportation access in terms of government savings on public assistance programs. My analysis in Table 5 shows that the availability of improved transportation led to a 0.8 percentage point reduction in SSI receipt among people with disabilities. There were approximately 11.3 million people with disabilities aged 22-54 in 2019 (ACS) so this corresponds with approximately 90,400 fewer individuals receiving SSI.

According to the Center on Budget and Policy Priorities (2024), more than half of adults age 18-64 report that they had no other income apart from SSI and subsequently were eligible to receive the maximum SSI benefit amount each month - $771 in 2019 (Social Security

[19]Note that this is a simple 2x2 TWFE with one pre-period year and one post-period. Cities that do not yet have UberWAV are used as the control group.

Administration 2024). As an upper bound, if we assume that all 90,400 individuals who would no longer receive SSI after Uber's launch were receiving the maximum benefit, this reduction in SSI receipt would reduce government expenditures on SSI by approximately $70 million each month or over $840 million per year. As an alternative, if we assume that these 90,400 people are people who received the average SSI benefit in 2019 ($566 according to Social Security Administration (2020)) then the government would save around $51 million a month or more than $612 million annually. These are direct savings, but the broader federal benefits could be even larger if we consider the increased tax revenues from increased earnings and potential reduced reliance on other social welfare programs.

Recent surveys provide information on the typical monthly ride-share utilization for people with disabilities. According to the Federal Highway Administration (2022), about 22% of both respondents with and without "travel limiting disabilities" used any form of ride-share service in the past month. On average, individuals with disabilities who used ride-share services took approximately five trips per month, slightly more than the four trips per month taken by individuals without disabilities. The average cost of an Uber in 2019 was around $25 per ride, resulting in an average monthly cost of $125. Comparing this cost to the potential savings in government expenditures highlights the efficiency gains from Uber's role as a backup transportation option. The average cost of $125 per month in Uber rides is substantially less than the $771 per month in SSI benefits that individuals would otherwise receive. As an upper bound if we were to assume that all people who were no longer on SSI *did* use Uber, and used it five times a month, the total monthly amount spent on ride-share services would be slightly more than $11 million.

To extend this cost exercise further, I can calculate the average expected ride-share expense for all people who gained employment due to the availability of improved transportation. A 1.4 percentage point increase in employment means that approximately 158,000 people are now employed based on the 2019 population. Even at nearly double the amount of people as above, the total monthly expense on ride-share services after assuming everyone uses Uber 5 times per month would be $20 million. These transportation expenses fall well below both estimates of the reduction in public assistance - totaling less than half of the more conservative reduction. This demonstrates that, for a relatively low cost, improving transportation access plays a key role in enabling people with disabilities to participate in the labor market and reducing their reliance on public assistance.

Improving access to reliable and flexible transportation through services like Uber, alleviates a meaningful barrier that people with disabilities face. Prior to the introduction of ride-share services, traditional public transportation systems struggled to provide options that meet the unique needs of this population. This inefficiency led to underemployment and higher rates of reliance on government assistance programs. The rise of ride-sharing technology can be seen as a partial solution to this market failure. However, its availability is mostly limited to urban and more densely populated areas. In more rural places, people with disabilities are still reliant on traditional, often unreliable, transportation services. As my results have shown, the largest positive effects of improving access to flexible transportation occur in places with worse existing public transportation. This raises the question of whether the government should actively intervene to encourage the expansion of access to ride-sharing services for people with disabilities.

These rough calculations serve as an upper bound on what the government should be willing to pay, reflecting the significant fiscal externalities generated by improved transportation access for people with disabilities. While providing direct subsidies for ride-sharing may bring moral hazard concerns—such as over-utilization or misuse—it's worth noting that the government already provides federal subsidies to paratransit services, which, on average, cost substantially more per ride than Uber. Some cities have even recently begun partnering with ride-share companies in order to offer more flexible, on-demand options as part of their paratransit programs. These partnerships demonstrate a potential pathway for substituting funds from traditional paratransit towards more flexible and cost-effective ride-share options. Based on my calculations, such interventions may be not only equitable but also fiscally prudent.

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, social integration, and reduced dependence on public assistance. Employment and labor force participation rates increase for people with disabilities after the introduction of Uber (3.3% and 2.1% respectively), while public assistance receipt, particularly Supplemental Security Income (SSI), decreases (4.5%). Through supplemental analyses I can rule out that this employment increase is solely caused by the direct employment effect of the ride-share 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. The relatively low frequency of ride-sharing trips among this population, as reported by Federal Highway Administration 2022, suggests that Uber is being used as "reliability insurance"—a backup when other transportation options fail—rather than as a daily mode of transportation. 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 3.3%. Effect sizes across a variety of other studies range from 0 to 59%, with most studies reporting effects above 10%.[20] The smaller observed effect sizes among people

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

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 ride-sharing services. If improved transportation can help people with disabilities engage more fully in the workforce and reduce their reliance on public assistance, 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 ride-sharing 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.

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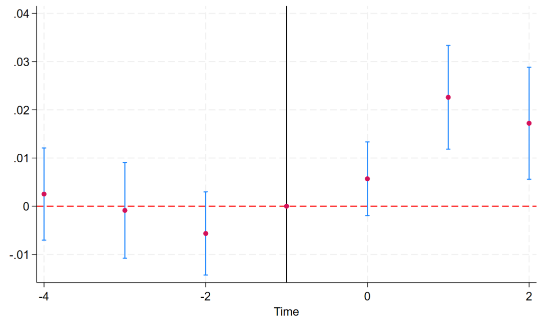
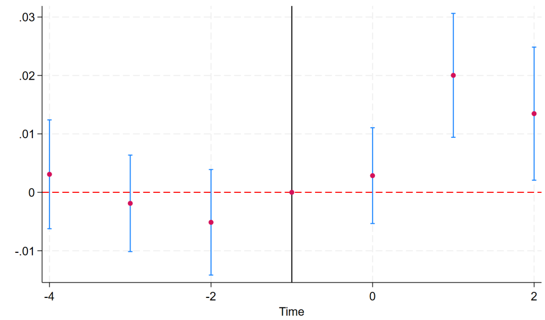
Tables and Figures

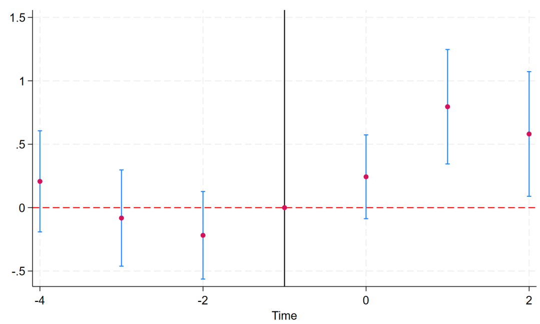
Figure 1: Event Studies - Main Outcomes



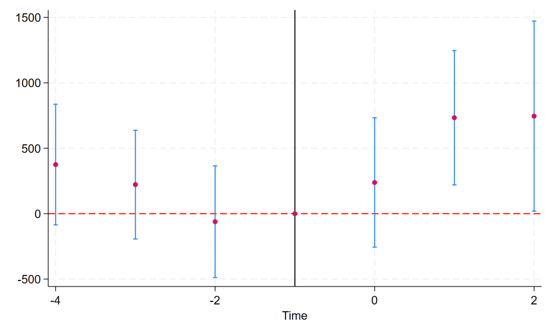
(a) Employment



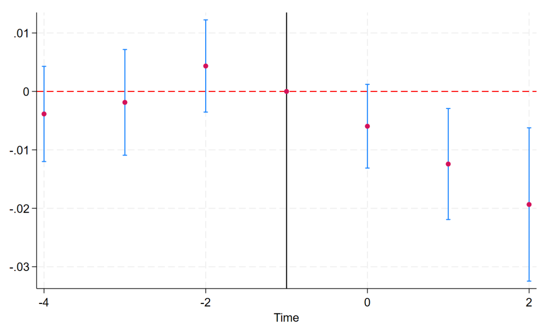
(b) Labor Force Participation



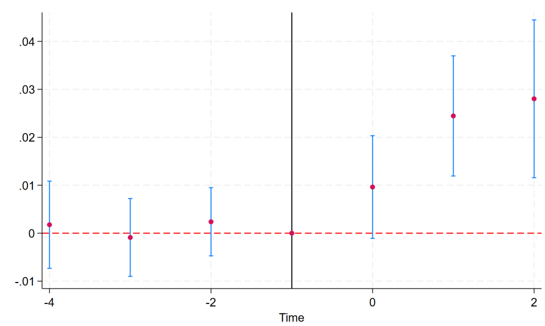
(c) Usual Hours Worked



(d) Wages



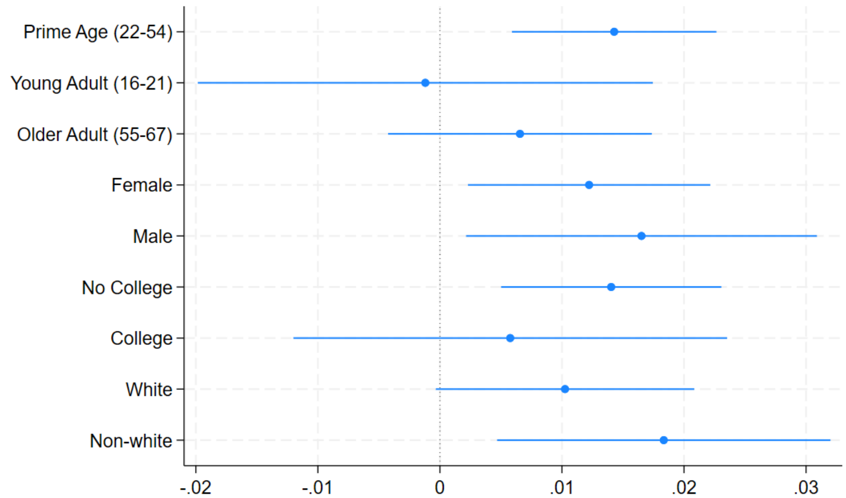
(e) Public Assistance



(f) Married

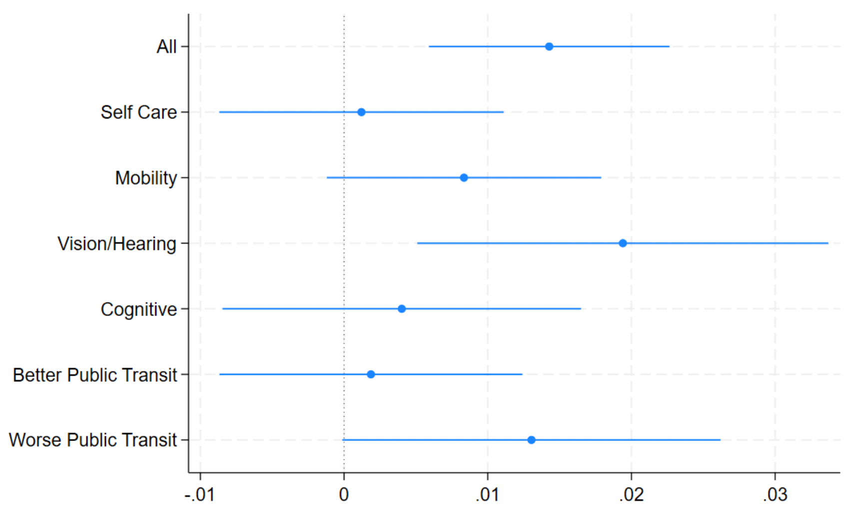
Note: Data are from the American Community Survey, restricted to individuals who report having a disability. Standard errors are clustered at the CBSA-level. All models include fixed effects for CBSA and year. Figures presents coefficients and 95% confidence intervals from an event study specification. 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



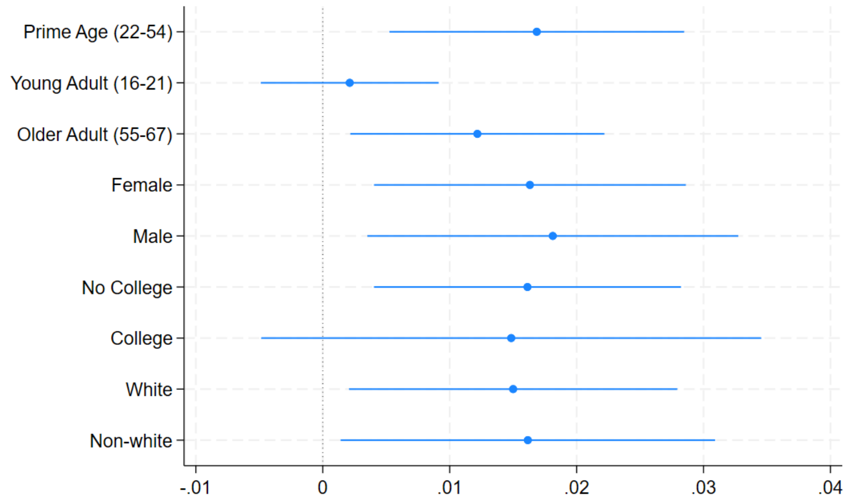
Note: Data are from the American Community Survey, restricted to individuals who report having a disability, 2006-2016. Standard errors are clustered at the CBSA-level. All models use equation (1) and include fixed effects for CBSA and year. Outcome is a binary measure = 1 if an individual is employed and zero otherwise. Each row reports the coefficient on $UberAvailable$ in a model that only includes the subgroup listed on the y-axis.

Figure 3: Disability Heterogeneity: Employment



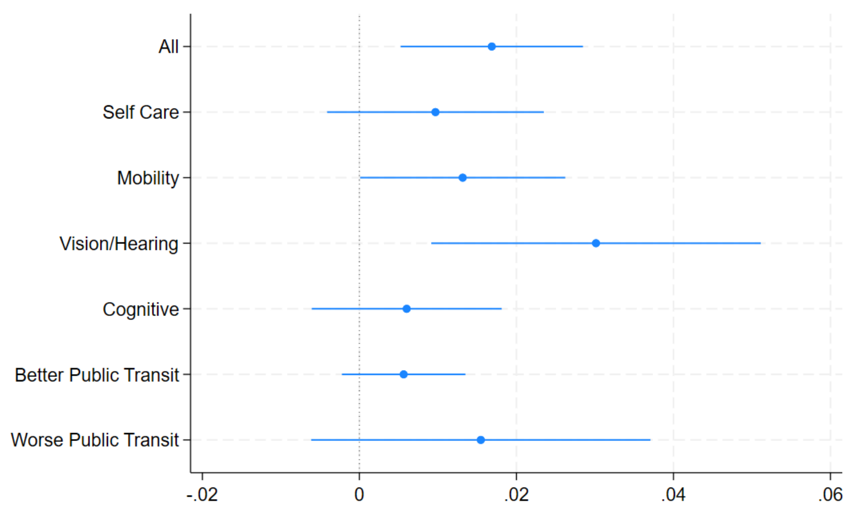
Note: Data are from the American Community Survey, restricted to individuals age 22-54 who report having a disability, 2006-2016. Standard errors are clustered at the CBSA-level. All models use equation (1) and include fixed effects for CBSA and year. Outcome is a binary measure = 1 if an individual is employed and zero otherwise. Each row reports the coefficient on $UberAvailable$ 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, 2006-2016. Standard errors are clustered at the CBSA-level. All models use equation (1) and include fixed effects for CBSA and year. Outcome is a binary measure = 1 if an individual is married and zero otherwise. Each row reports the coefficient on *UberAvailable* 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 age 22-54 who report having a disability , 2006-2016. Standard errors are clustered at the CBSA-level. All models use equation (1) and include fixed effects for CBSA and year. Outcome is a binary measure = 1 if an individual is married and zero otherwise. Each row reports the coefficient on *UberAvailable* 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	0.414	0.801
	(0.493)	(0.399)
Labor Force Participation	0.497	0.860
	(0.500)	(0.347)
Wage Income	15,078.27	39,268.56
	(30,972.97)	(52,386.99)
Total Income	21,770.45	43,180.30
	(33,680.67)	(56,494.57)
Share with Public Assistance	0.233	0.020
	(0.423)	(0.140)
Age	41.269	37.708
	(9.575)	(9.483)
Share with at Least a College Degree	0.143	0.354
	(0.350)	(0.478)
Share Moved in Last Year	0.176	0.178
	(0.381)	(0.383)
Share Living in a HH with Kids	0.349	0.477
	(0.477)	(0.499)
Share Living with Parents	0.200	0.131
	(0.400)	(0.337)
Share Married	0.360	0.531
	(0.480)	(0.499)
Share with Self Care or Independent Living Disability	0.384	
	(0.486)	
Share with Mobility Disability	0.475	
	(0.499)	
Share with Vision/Hearing Disability	0.309	
	(0.462)	
Share with Cognitive Disability	0.451	
	(0.498)	
Observations	570,764	7,169,379

Note: Data are from the American Community Survey 2006-2016. The sample is restricted to individuals age 22-54. Standard deviations in parentheses.

Table 2: 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 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 3: Main Results - Full Sample

	(1) Employed	(2) Labor Force	(3) Usual Hours	(4) Wages	(5) Public Assistance	(6) Married
Uber Available	0.014***	0.011**	0.491***	335.878	-0.010**	0.017***
	(0.004)	(0.004)	(0.188)	(232.468)	(0.004)	(0.006)
Observations	809,350	809,350	809,350	809,350	809,350	809,350
Control Mean†	0.423	0.503	16.301	13646.142	0.221	0.392
CBSA and Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Table uses individual-level data from the 2006-2016 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. 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 4: Supplemental Employment Results

	(1) Wages Over 5,000	(2) Wages Over 10,000	(3) Wages Over 20,000	(4) Hours Over 5	(5) Hours Over 20	(6) Hours Over 40	(7) Occ: Transport	(8) Self Emp
Uber Available	0.013***	0.010**	0.003	0.014***	0.012***	0.009**	0.000	0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)
Observations	809,350	809,350	809,350	809,350	809,350	809,350	809,350	809,350
Control Mean†	0.413	0.358	0.259	0.419	0.392	0.286	0.059	0.057
CBSA and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Table uses individual-level data from the 2006-2016 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. Coefficients for $Uber_{cs}$ and $Post_{ts}$ are excluded from these tables in the interest of space. Wages 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 5: Supplemental Income and Household Composition Results

	(1) Public Assistance	(2) Soc. Sec.	(3) Welfare	(4) SSI	(5) Total Income	(6) Kids	(7) Live with Parents	(8) Unmarried Partner
Uber Available	-0.010**	-0.006*	-0.001	-0.008**	-111.603	0.008	-0.004	-0.002
	(0.004)	(0.003)	(0.002)	(0.004)	(275.050)	(0.005)	(0.004)	(0.002)
Observations	809,350	809,350	809,350	809,350	809,350	809,350	809,350	809,350
Control Mean†	0.221	0.175	0.060	0.181	19994.960	0.358	0.164	0.071
CBSA and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Table uses individual-level data from the 2006-2016 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. Coefficients for $Uber_{cs}$ and $Post_{ts}$ are excluded from these tables in the interest of space. Public Assistance is a binary variable = 1 if a person receives any income from public assistance, Soc. Sec 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, 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. †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 6: 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	0.014***	0.011**	0.491***	335.878	-0.010**	0.017***
	(0.004)	(0.004)	(0.188)	(232.468)	(0.004)	(0.006)
Observations	809,350	809,350	809,350	809,350	809,350	809,350
Control Mean†	0.423	0.503	16.301	13646.142	0.221	0.392
Young Adult (16-21)						
Uber Available	-0.001	0.005	0.249	63.382	-0.002	0.002
	(0.009)	(0.012)	(0.256)	(173.250)	(0.008)	(0.004)
Observations	101,662	101,662	101,662	101,662	101,662	101,662
Control Mean†	0.270	0.415	7.279	2691.712	0.151	0.028
Older Adult (55-67)						
Uber Available	0.007	0.006	0.180	21.174	-0.005	0.012**
	(0.005)	(0.006)	(0.212)	(279.779)	(0.005)	(0.005)
Observations	721,349	721,349	721,349	721,349	721,349	721,349
Control Mean†	0.281	0.311	10.518	10420.577	0.161	0.532
CBSA and Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Table uses individual-level data from the 2006-2016 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. 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 7: 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***	0.013*	0.572	390.044	-0.014**	0.030***
	(0.007)	(0.006)	(0.348)	(530.176)	(0.006)	(0.011)
Observations	250,593	250,593	250,593	250,593	250,593	250,593
Control Mean†	0.552	0.632	22.201	19815.032	0.162	0.448
Mobility						
Uber Available	0.008*	0.008	0.352	121.694	-0.006	0.013**
	(0.005)	(0.006)	(0.220)	(244.450)	(0.005)	(0.007)
Observations	382,429	382,429	382,429	382,429	382,429	382,429
Control Mean†	0.336	0.403	12.963	10792.658	0.240	0.412
Self Care						
Uber Available	0.001	0.002	-0.004	-12.766	-0.012*	0.010
	(0.005)	(0.005)	(0.193)	(226.975)	(0.006)	(0.007)
Observations	317,224	317,224	317,224	317,224	317,224	317,224
Control Mean†	0.225	0.282	7.809	6426.684	0.335	0.334
Cognitive						
Uber Available	0.004	0.002	0.142	93.915	-0.008	0.006
	(0.006)	(0.005)	(0.249)	(286.645)	(0.007)	(0.006)
Observations	361,302	361,302	361,302	361,302	361,302	361,302
Control Mean†	0.309	0.395	10.952	8157.751	0.312	0.291
CBSA and Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Table uses individual-level data from the 2006-2016 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. 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 8: 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	0.013*	0.011	0.522*	867.391***	-0.005	0.015
	(0.007)	(0.007)	(0.282)	(329.272)	(0.007)	(0.011)
Observations	406,584	406,584	406,584	406,584	406,584	406,584
Control Mean†	0.427	0.506	16.510	13,652.28	0.212	0.412
Better Local Public Transportation						
Uber Available	0.002	-0.002	-0.095	-569.045	-0.001	0.006
	(0.005)	(0.006)	(0.256)	(353.357)	(0.004)	(0.004)
Observations	401,660	401,660	401,660	401,660	401,660	401,660
Control Mean†	0.419	0.499	16.021	13,674.78	0.234	0.362
CBSA and Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Table uses individual-level data from the 2006-2016 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. 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 9: Main Robustness Checks

	(1) Employed	(2) Labor Force	(3) Usual Hours	(4) Wages	(5) Public Assistance	(6) Married
Includes CBSA-specific Linear Time Trend						
Uber Available	0.016***	0.008*	0.653***	704.096**	-0.005	0.009
	(0.005)	(0.005)	(0.228)	(300.309)	(0.005)	(0.007)
Observations	809,350	809,350	809,350	809,350	809,350	809,350
Includes Lagged Timing						
Uber Available	0.014***	0.011**	0.501**	296.287	-0.010**	0.017***
	(0.005)	(0.005)	(0.202)	(246.373)	(0.004)	(0.006)
Uber Available Next Year	0.001	0.001	0.045	-177.055	0.001	-0.003
	(0.004)	(0.004)	(0.150)	(167.270)	(0.004)	(0.003)
Observations	809,350	809,350	809,350	809,350	809,350	809,350
Include Controls						
Uber Available	0.016***	0.008**	0.606***	273.593	-0.011***	0.017***
	(0.004)	(0.004)	(0.199)	(274.535)	(0.004)	(0.006)
Observations	809,350	809,350	809,350	809,350	809,350	809,350
Remove Early Cohorts						
Uber Available	0.021**	0.012*	0.588*	427.336	-0.015**	0.029***
	(0.008)	(0.007)	(0.319)	(340.217)	(0.007)	(0.011)
Observations	329,149	329,149	329,149	329,149	329,149	329,149

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 use equation (1) and include fixed effects for CBSA and year. 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. Treat 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; individual-level controls include: age, and indicators for female, nonwhite, and college degree. The sample for the panel that removes early cohorts excludes the 2010 and 2011 treatment cohorts. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

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 Z. 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. 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 ride-sharing 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 quite 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:

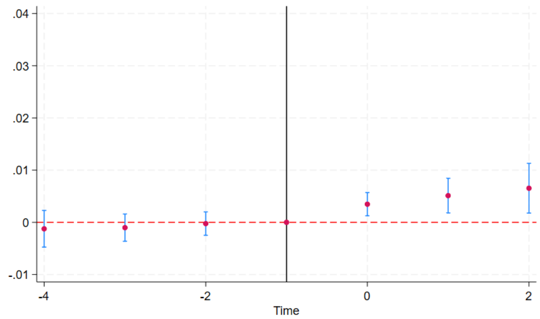
$$\begin{aligned} Y_{icts} = {} & \alpha_c + \gamma_t + \beta_1 Uber_{cs} + \beta_2 Post_{ts} + \beta_3 UberAvailable_{cts} \\ & + \beta_4 Disability_{icts} + \beta_5 Uber_{cs} * Disability_{icts} + \beta_6 Post_{ts} * Disability_{icts} \\ & + \beta_7 UberAvailable_{cts} * Disability_{icts} + \epsilon_{ict} \end{aligned} \quad (2)$$

where Y_{icts} represents outcomes for individual i in CBSA c at time t in stack s, α_c are CBSA fixed effects, γ_t are year fixed effects, and the standard errors are clustered at the CBSA level. For the purposes of this analysis, I limit the outcomes to employment, labor force participation, public assistance receipt, and marriage as those are the primary results for the disabled population. $Uber_{cs}$ is a binary variable equal to one if CBSA c was part of cohort that got Uber in stack s, and zero otherwise. $Post_{ts}$ is a binary variable equal to one if year t in stack s is a year greater than or equal to the launch year. $UberAvailable_{cts}$

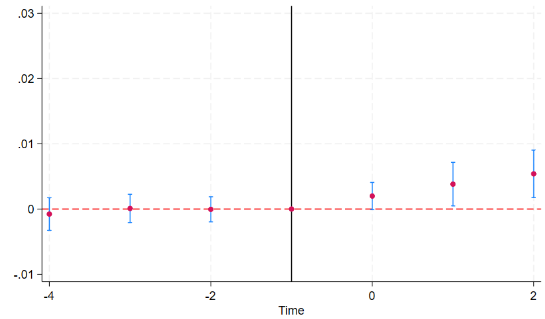
is the interaction between $Uber_{cs}$ and $Post_{ts}$, this term is a binary variable that equals one if CBSA c obtains Uber in stack s and the year t is after the launch. $Disability_{icts}$ is a binary variable equal to one if the person answered affirmatively to any of the ACS questions related to disability status. The coefficient of interest is β_7 which measures the impact of the availability of flexible and reliable transportation for people with disabilities relative to people without disabilities.

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. This suggests that while improved transportation access has meaningful economic and social effects across the entire population, these effects are much stronger among a vulnerable group with potentially fewer alternative transportation options. These results also reveal that the conclusions of the cost-benefit analysis in Section 4.5 would likely only be relevant for people with disabilities, as there are much smaller effects on public assistance for the non-disabled population.

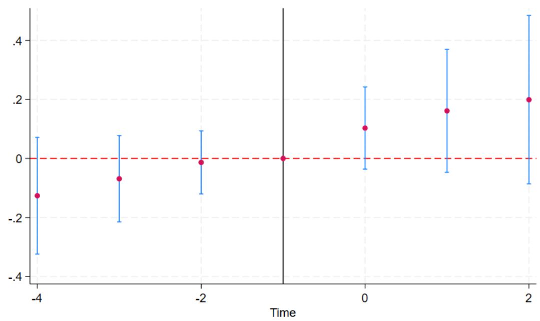
Figure B1: Event Studies - Main Outcomes for People without Disabilities



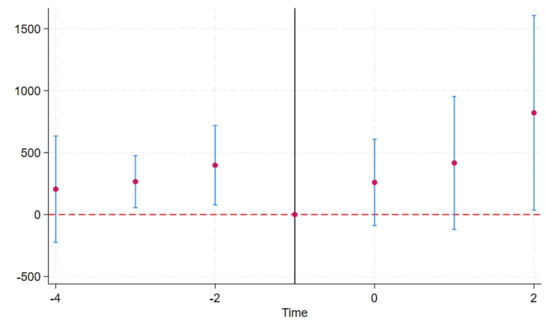
(a) Employment



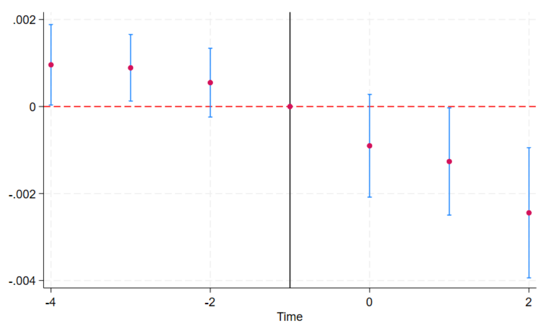
(b) Labor Force Participation



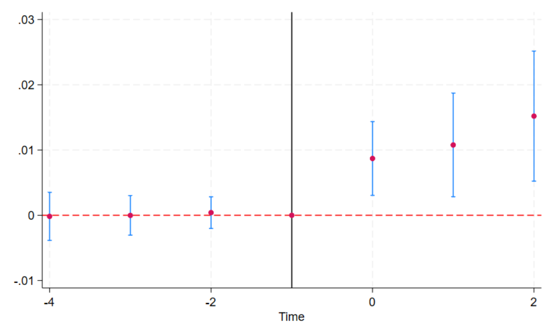
(c) Usual Hours Worked



(d) Wages



(e) Public Assistance



(f) Married

Note: Data are from the American Community Survey, restricted to individuals who do not report having a disability. Standard errors are clustered at the CBSA-level. All models include fixed effects for CBSA and year. 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.

Table B1: Triple Difference-in-Difference

VARIABLES	(1) Employed	(2) Labor Force	(3) Public Assistance	(4) Married
Uber Available	0.005***	0.003**	-0.001	0.010***
	(0.002)	(0.001)	(0.001)	(0.003)
Uber Available*Disability	0.015***	0.014***	-0.021***	0.009**
	(0.004)	(0.004)	(0.004)	(0.004)
Observations	10,294,570	10,294,570	10,294,570	10,294,570
CBSA and Year FE	Yes	Yes	Yes	Yes

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. Coefficients for $Uber_{cs}$, $Post_{ts}$, and all 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:

$$Y_{ict} = \alpha_c + \gamma_t + \beta_3 UberWAVAvailable_{ct} + \epsilon_{ict} \tag{3}$$

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.

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.

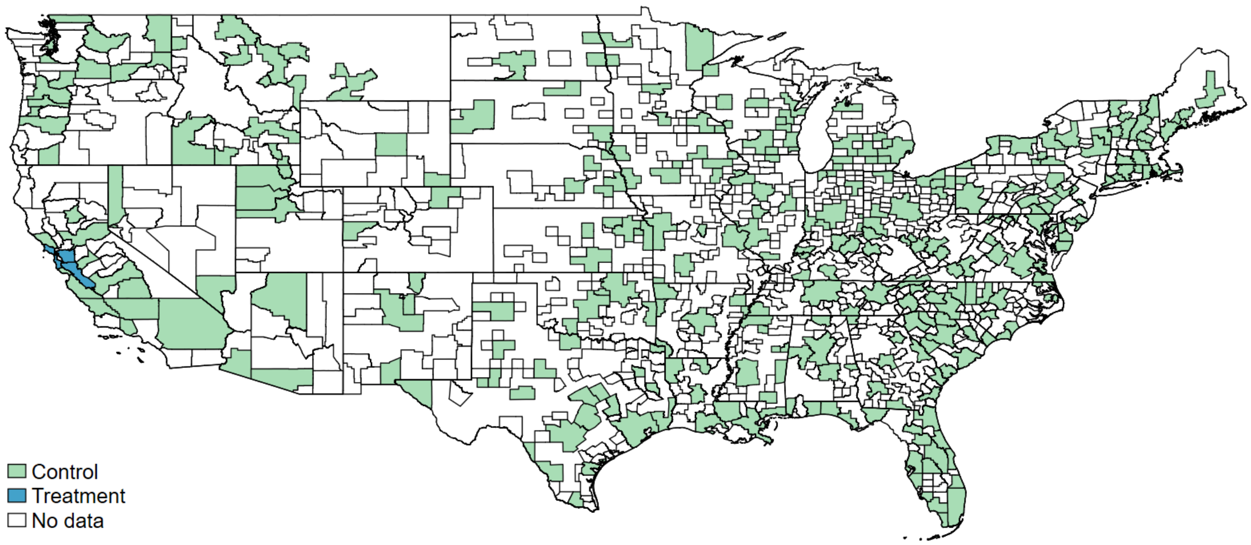
Table C2: UberWAV Results

VARIABLES	(1) Employed	(2) Labor Force	(3) Public Assistance	(4) 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
Controls?	No	No	No	No

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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

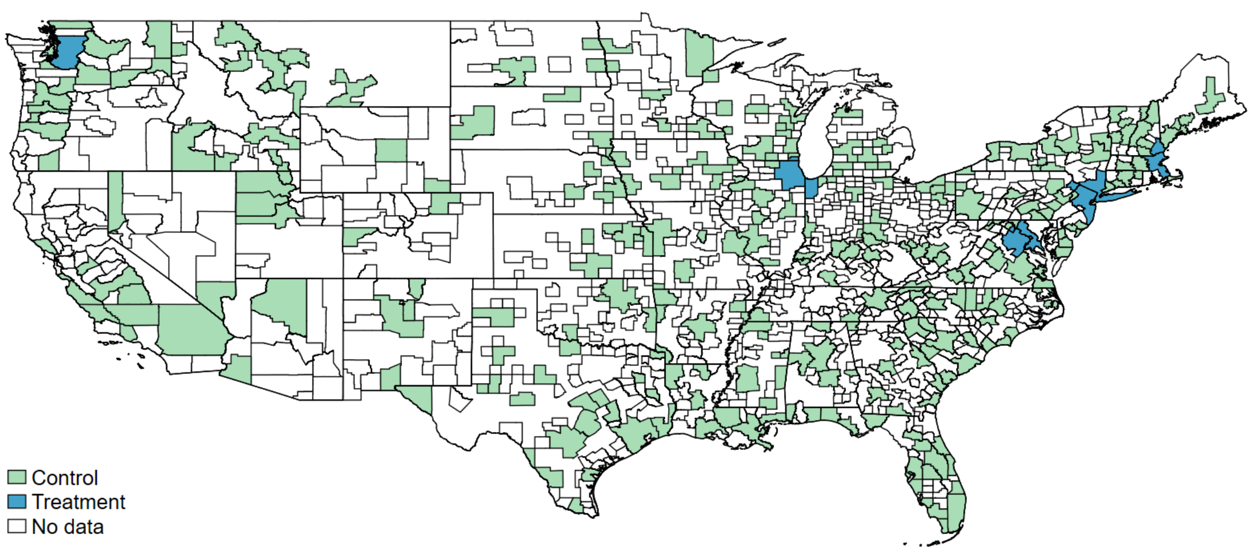
D Supplemental Tables and Figures

Figure D1: 2010 Cohort Treatment Variation



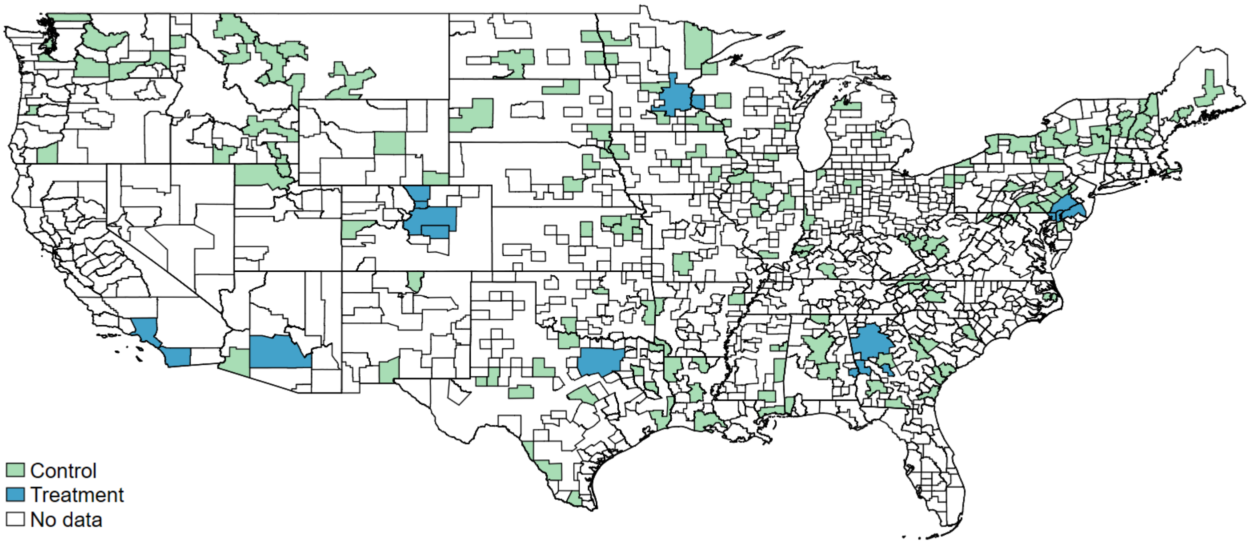
Note: Start date data are from Hall and Krueger (2018). Map shows the cities that were treated in 2010 and the cities that are used in the control group for that cohort (who received Uber in 2013 or later).

Figure D2: 2011 Cohort Treatment Variation



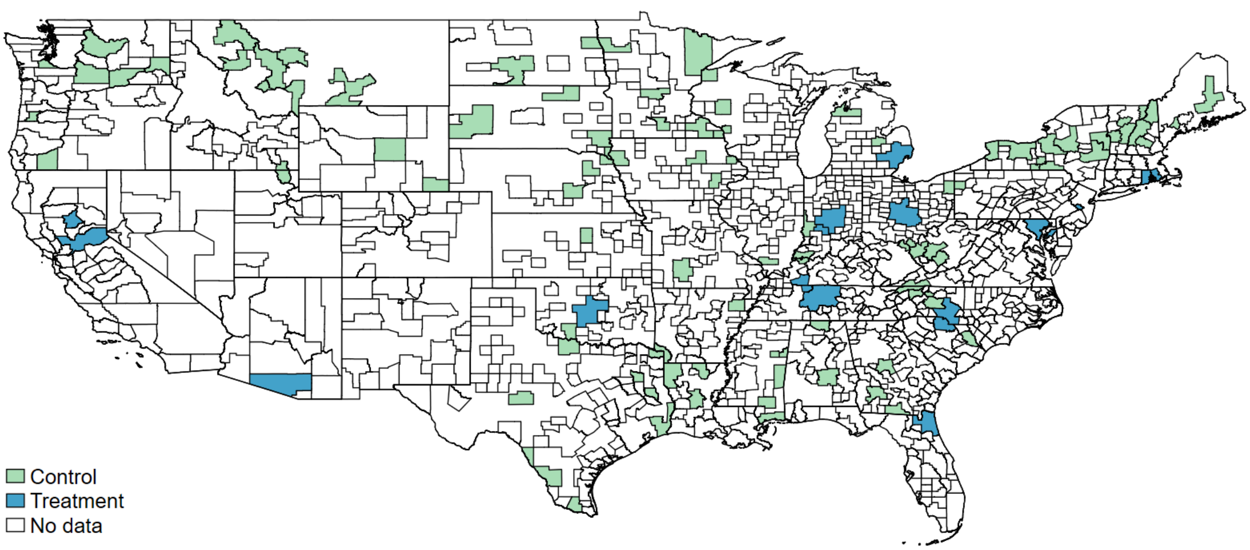
Note: Start date data are from Hall and Krueger (2018). Map shows the cities that were treated in 2011 and the cities that are used in the control group for that cohort (who received Uber in 2014 or later).

Figure D3: 2012 Cohort Treatment Variation



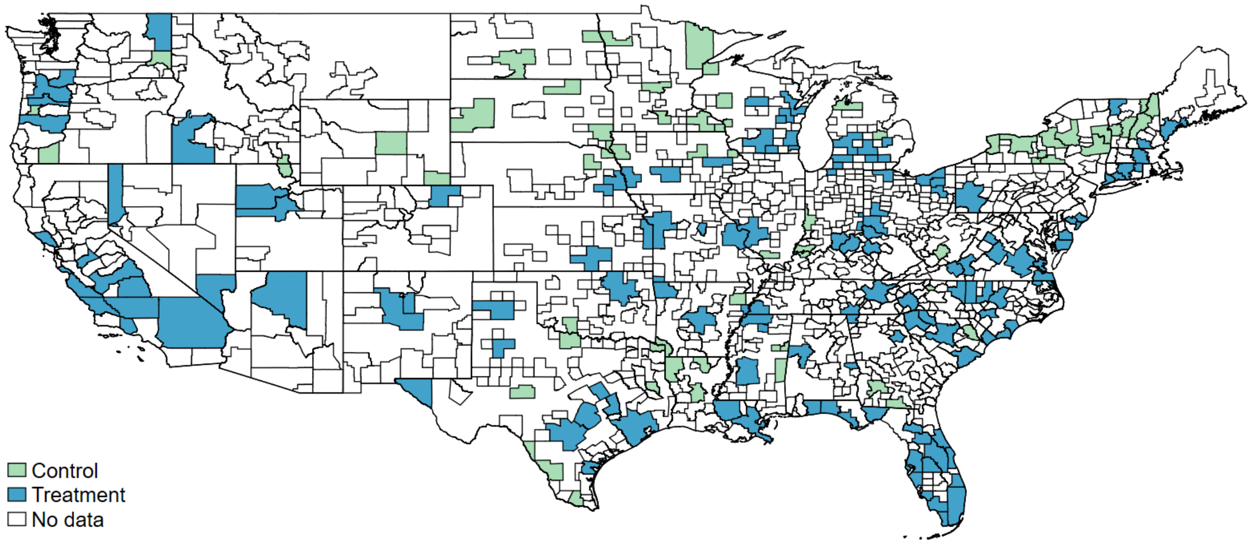
Note: Start date data are from Hall and Krueger (2018). Map shows the cities that were treated in 2012 and the cities that are used in the control group for that cohort (who received Uber in 2015 or later).

Figure D4: 2013 Cohort Treatment Variation



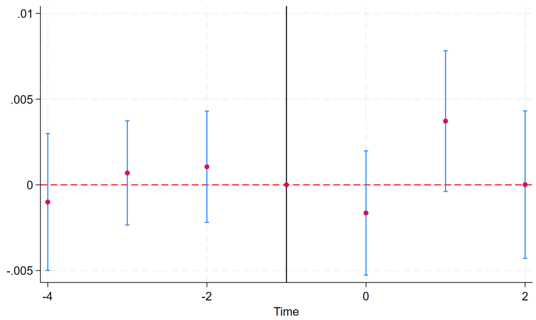
Note: Start date data are from Hall and Krueger (2018). Map shows the cities that were treated in 2013 and the cities that are used in the control group for that cohort (who received Uber in 2016 or later).

Figure D5: 2014 Cohort Treatment Variation

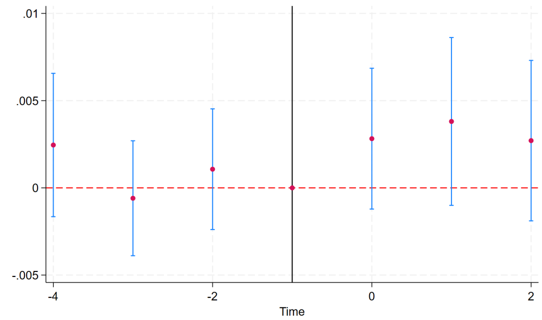


Note: Start date data are from Hall and Krueger (2018). Map shows the cities that were treated in 2014 and the cities that are used in the control group for that cohort (who received Uber in 2017 or later).

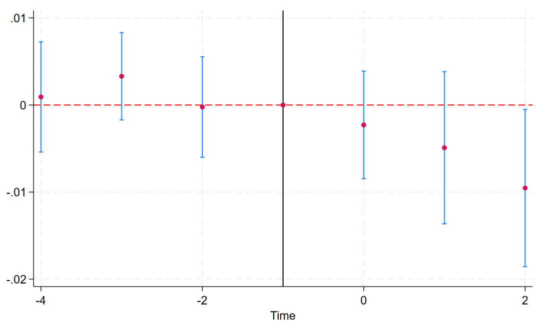
Figure D6: Event Studies - Supplemental Employment and Income Outcomes



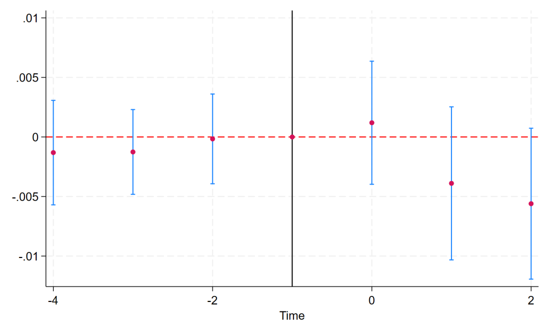
(a) Transportation Occupations



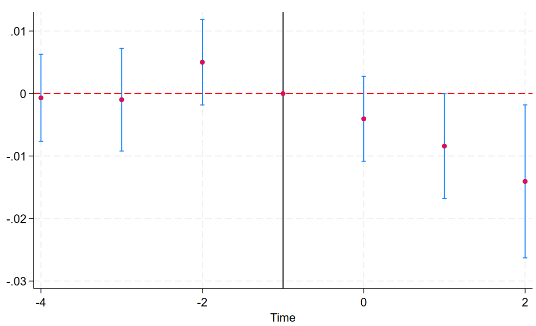
(b) Self Employment



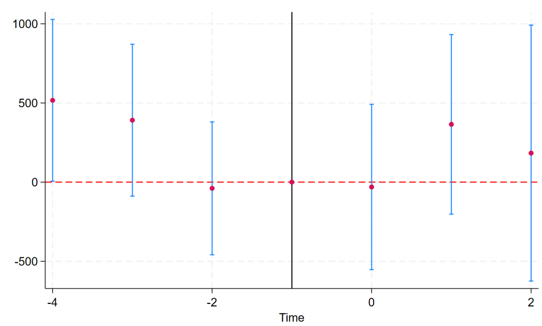
(c) Social Security



(d) Welfare



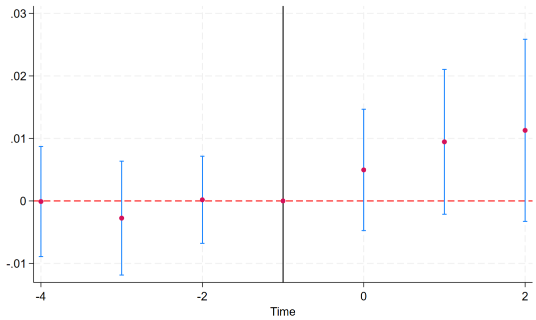
(e) SSI



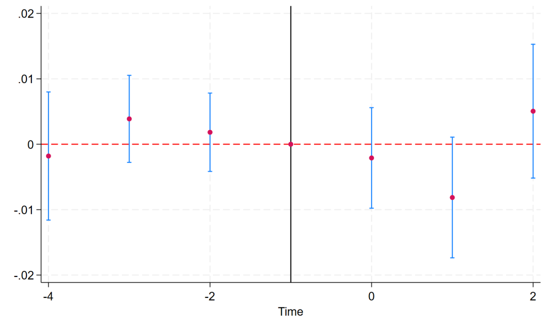
(f) Total Income

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. 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. 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.

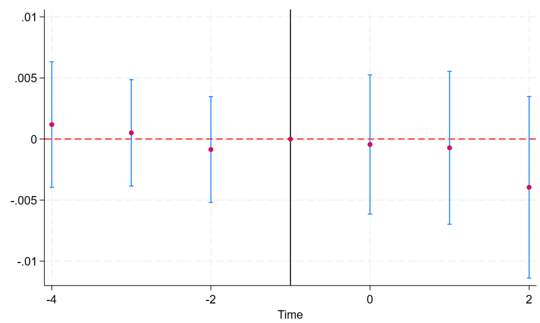
Figure D7: Event Studies - Supplemental Household Composition Outcomes



(a) Living in a Household with Kids



(b) Living with Parents



(c) Living with Unmarried Partner

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. 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.

Table D1: Main Results - Race and Gender Heterogeneity

	(1) Employed	(2) LabForce	(3) Usual Hours	(4) Wages	(5) Public Assistance	(6) Married
White						
Uber Available	0.010*	0.008	0.420*	472.138	-0.006	0.015**
	(0.005)	(0.005)	(0.227)	(314.415)	(0.005)	(0.007)
Observations	566,464	566,464	566,464	566,464	566,464	566,464
Control Mean†	0.443	0.518	17.162	14961.020	0.201	0.421
Non-white						
Uber Available	0.018***	0.013	0.517*	-23.335	-0.015**	0.016**
	(0.007)	(0.008)	(0.272)	(335.291)	(0.006)	(0.007)
Observations	241,780	241,780	241,780	241,780	241,780	241,780
Control Mean†	0.375	0.468	14.208	10464.218	0.271	0.320
Male						
Uber Available	0.017**	0.015**	0.635*	761.876*	-0.009*	0.018**
	(0.007)	(0.007)	(0.331)	(418.263)	(0.005)	(0.007)
Observations	385,496	385,496	385,496	385,496	385,496	385,496
Control Mean†	0.460	0.550	18.663	17002.119	0.195	0.389
Female						
Uber Available	0.012**	0.008	0.359*	-99.128	-0.010*	0.016***
	(0.005)	(0.005)	(0.193)	(246.001)	(0.006)	(0.006)
Observations	422,748	422,748	422,748	422,748	422,748	422,748
Control Mean†	0.389	0.459	14.064	10477.727	0.246	0.394
CBSA and Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Table uses individual-level data from the 2006-2016 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. 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 D2: Main Results - Educational Attainment Heterogeneity

	(1) Employed	(2) LabForce	(3) Usual Hours	(4) Wages	(5) Public Assistance	(6) Married
No College Degree						
Uber Available	0.014***	0.011**	0.411**	113.128	-0.009**	0.016***
	(0.005)	(0.004)	(0.186)	(199.110)	(0.005)	(0.006)
Observations	696,371	696,371	696,371	696,371	696,371	696,371
Control Mean†	0.396	0.479	14.992	11173.032	0.238	0.376
College Degree						
Uber Available	0.006	0.006	0.556	242.620	-0.006	0.015
	(0.009)	(0.009)	(0.495)	(1,012.016)	(0.005)	(0.010)
Observations	111,873	111,873	111,873	111,873	111,873	111,873
Control Mean†	0.638	0.695	26.457	32844.312	0.088	0.507
CBSA and Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Table uses individual-level data from the 2006-2016 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. 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 D3: Robustness Check: Predict Timing

	(1)	(2)	(3)	(4)	(5)	(6)
Lag Employed	0.432					
	(1.017)					
Lag Labor Force Participation		-1.052				
		(1.178)				
Lag Usual Hours			0.024			
			(0.024)			
Lag Wages				-0.000		
				(0.000)		
Lag Public Assistance					-0.907	
					(1.403)	
Lag Married						0.277
						(1.177)
Observations	179	179	179	179	179	179

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 in that CBSA in the year prior to getting Uber. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table D4: Robustness Check: Composition

	(1) Migration	(2) Disability
Uber Available	0.002	-0.001
	(0.004)	(0.001)
Observations	809,350	10,294,570
Control Mean†	0.189	0.087
CBSA and Year FE	Yes	Yes

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. Coefficients for $Uber_{cs}$ and $Post_{ts}$ are excluded from these tables in the interest of space. Column (1) reports the effects on migration, a binary variable = 1 if a person moved in the last 5 years, for people with disabilities. Column (2) presents results on the proportion of people who have a disability (an indicator variable = 1 if a person responds that they have any disability). †The control mean reports the mean of each outcome in the pre-period years for the control observations in each cohort. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$