Alternative Insurance: Gig Work and Social Insurance Participation*

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October 28, 2025

Abstract

Flexible gig opportunities provide a new means for workers to self-insure against negative economic shocks. Exploiting the roll-out of Uber, we use difference-in-differences and staggered treatment timing methods to show that access to flexible gig arrangements reduces participation in public assistant programs like Social Security Disability Insurance, Supplemental Security Income, and Supplemental Nutrition Assistance Program. To some extent, this new form of private self-insurance crowds-out traditional social insurance. However, the effect of gig opportunity access on program participation is attenuated in weak local labor markets, meaning that gig work does not replace social programs when insuring against aggregate, macroeconomic risks.

Keywords: gig work, social insurance, insurance

JEL Codes: I38, R23, H55, G52

*We thank participants at WEAI 2025 and Melissa Gentry, Bradley Heim, Lars Lefgren, and Joe Price for helpful comments, discussions, and feedback. This work was in part generously funded through SSA University of Wisconsin Madison RDRC grant number WI25-06.

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1 Introduction

Over the past 15 years, the gig economy has expanded rapidly, with millions of workers engaging in task-based, platform-mediated work (i.e., gig work). Gig work encompasses a wide range of work including driving for ride-hailing services such as Uber and Lyft, food delivery, digital marketing, freelance writing, data entry, survey taking, and tutoring. In the US, a significant portion of the workforce is involved in some sort of gig work, with estimates ranging from 2% to 40%.[1] Among those with gig income, 58% report that it was essential or important for meeting their basic needs (Pew Research Center, 2021).

Unlike traditional employment, gig work is designed to offer workers control over their schedules (Chen et al., 2017; Mas and Pallais, 2017), immediate income through on-demand pay, and a way to supplement or replace earnings without undergoing formal hiring processes. These features have made gig work especially attractive to people who are unemployed, underemployed, near retirement, disabled, or struggling to balance caregiving responsibilities.[2] Because of this flexibility, individuals might use gig opportunities as a way to self-insure against negative economic shocks. If an individual loses their job or is unable to continue a traditional employment relationship due to injury, disability, or other causes, they can quickly and flexibly start earning income at their own pace through gig work to smooth income losses. The advent of gig opportunities has the potential to displace formal social programs as a preferred means of insuring against adverse shocks for some individuals, suggesting a new dimension of crowd-out. The extent of this substitution is an empirical question.

In this paper, we investigate whether access to gig employment opportunities, as proxied by Uber's staggered entry into U.S. counties, affects participation in public social insurance and welfare programs including the Social Security Disability Insurance (SSDI), Supplemen-

[1] See (Abraham et al., 2018; Bracha and Burke, 2018; Collins et al., 2019; Farrell and Greig, 2016; Gallup, 2018; United States Government Accountability Office, 2017).

[2] See (Abraham, Hershbein and Houseman, 2021; Chen et al., 2017; Huang et al., 2020; Katz and Krueger, 2019; Khan et al., 2024; Koustas, 2019; Oyer, 2020; Watson et al., 2021).

tal Security Income (SSI), the Supplemental Nutrition Assistance Program (SNAP), and Medicaid. We then document how the substitution between gig employment as a form of self-insurance and traditional social insurance varies with local economic conditions to better understand to what extent this new form of flexible self-insurance crowds out social insurance.

Using Uber's entry into local markets as a natural experiment in a two-way fixed effects (TWFE) design, we compare changes in welfare receipt and income in counties before and after Uber's entry, relative to counties where Uber had not yet launched. Drawing on three different datasets - county-level administrative programmatic caseload data, individual-level American Community Survey (ACS) data, and the Health and Retirement Study linked to Social Security Benefits administrative data (HRS-SSB data), we find gig access increases the prevalence of gig work, and simultaneously leads to robust declines of 2 to 5 percent in social welfare program participation, especially SSDI, SSI, and SNAP. Estimates are consistent when using stacked panel regressions and doubly robust difference-in-differences methods designed to address concerns about two-way fixed effects strategies with staggered treatment timing (Callaway and Sant'Anna, 2020; Goodman-Bacon, 2020). This finding suggests that when flexible gig work arrangements are available, some individuals substitute away from participation in formal social insurance programs to self-insurance through flexible gig work. This pattern of substitution has an impact on the structure of social insurance programs. We estimate that the nationwide roll-out of gig opportunities reduced both SSDI and SSI enrollment by over one hundred thousand people, and reduced government spending on these programs by approximately two billion dollars each.

However, the effect of access to gig opportunities on program participation is attenuated when local economies face unfavorable economic conditions (i.e., high unemployment rates), suggesting that gig work is a limited form of self-insurance and less effective at mitigating broader macroeconomic risks. These findings indicate that while flexible work arrangements may enable individuals to smooth idiosyncratic shocks like disability or job-loss, social in-

surance and safety net programs remain essential as automatic stabilizers when there are macroeconomic downturns.

Despite a large, recent literature exploring how the gig economy is changing labor market structure (Abraham et al., 2019; Abraham, Hershbein and Houseman, 2021; Collins et al., 2019; Garin et al., 2023; Katz and Krueger, 2019), little is known about how the availability of gig work influences households' reliance on the social safety net. On one hand, gig work may offer a flexible source of income that allows individuals to reduce their participation in public assistance programs and instead self-insure. On the other hand, these jobs often lack benefits, job security, and stable earnings, raising questions about whether they represent a viable pathway to economic self-sufficiency or merely shift welfare program dependence to a later date.

Our study builds on and contributes to the literature in several ways. First, we provide new evidence on the interaction between gig work and the welfare state, a topic of growing relevance as policymakers consider how to adapt social insurance systems to an evolving labor market. Several recent studies have examined the impact of Uber and other gig platforms on employment, wages, traffic safety, and consumer welfare (Berger et al., 2022; Cook et al., 2020; Hall et al., 2020). However, only a few studies have investigated how the availability of gig work affects broader measures of household economic stability, such as participation in public assistance programs or shifts in the income distribution. Rutledge et al. (2018) shows descriptively, that gig workers in their 50s and 60s are 25% less likely to apply for and be awarded disability insurance, but it is unclear if this is simply selection or a causal relationship. Wilson (forthcoming) shows that self-employment responses to the Earned Income Tax Credit are larger when gig opportunities like Uber are available, while Gentry (2025) finds that access to Uber decreases disability insurance income among disabled individuals (plausibly by providing transportation to work). Rather than view the entry of Uber as simply a means of transportation, we focus on the fact that Uber's entry signifies an increase in gig opportunities more generally, not only for disabled workers but for the broader population

when they face economic shocks. Additionally, we show how the effects of gig opportunity access differ for other social programs and among older adults, a population that is increasingly engaging in nontraditional work as retirement insecurity becomes more prevalent in an aging population. Second, we show that substitution away from social insurance caused by access to gig work depends on local economic conditions, highlighting the benefits of having both formal and informal insurance means. To the best of our knowledge, no prior work has explored how local economic conditions affect substitution between gig opportunities and formal social insurance programs. Third, our use of Uber's staggered market expansion as a plausibly exogenous source of variation allows for credible identification of the effect of gig opportunity access on social program participation. Following the approach used in past work (Hall et al., 2018; Wilson, forthcoming), we exploit the fact that Uber's entry into counties was largely determined by strategic business considerations, regulatory factors, and technological readiness. Finally, we show that results are consistent across three complementary datasets: the county-level administrative data provide accurate records on welfare programs at county-level; the ACS provides a large, nationally representative sample allowing us to document heterogeneous effects and effects on income; the HRS-SSB enables us to combine individual-level survey and SSA administrative data to mitigate concerns about measurement error for a subset of older adults. These individual-level datasets allow us to examine both the general population and specific subgroups who may be more sensitive to changes in labor market conditions.

Our findings speak to fundamental questions about the role of gig work in contemporary economic life. If the entry of gig platforms reduces reliance on welfare programs and increases household income, this would suggest that gig work serves as an effective economic buffer during periods of job loss or economic downturns. Conversely, if gig work has little impact on or even increases program participation, it may indicate that the non-standard work arrangements of the platform economy actually increase economic risk and are not sustainable employment alternatives. We find that in the short run, access to gig work provides a viable

substitute to traditional social insurance programs for a subset of individuals, but this is less true when individuals face systemic economic shocks, like local economic downturns.

The remainder of this paper is structured as follows. Section 2 discusses the potential self-insurance role of gig work and describes the gig economy setting. Section 3 describes our data sources. Section 4 provides empirical strategy. Section 5 presents our main results, robustness, and heterogeneity analyses, while Section 6 concludes.

2 Motivation

Social programs are designed to insure individuals and households against risks that might be hard to insure against privately, such as a work inhibiting disability or income loss due to a lay-off or an economic downturn. If individuals are risk adverse and unable to insure privately, the provision of social insurance will improve welfare and be efficient. If individuals *are* able to privately insure against risks, access to public, social insurance might simply crowd-out private actions. The advent of gig work, which provides access to short-term, flexible work generally with few entry barriers might increase individuals' and families' ability to privately insure against these risks, leading to potential welfare implications for social insurance. This is consistent with previous work that has found that people use gig work, specifically ride share, to smooth consumption when they lose more traditional payroll work (Koustas, 2020). The opportunity to flexibly earn money through a gig platform could shift people away from social program participation.

For example, if a worker loses their job, becomes disabled, or faces some other idiosyncratic shock that reduces their income they can choose to participate in social programs which offer a benefit, but also impose costs, such as stigma, ordeal mechanisms (Nichols and Zeckhauser, 1982), and means-testing requirements. In the gig economy, workers can smooth temporary shocks by picking up flexible gig work, which provide income but also imposes costs such as reduced leisure or job related costs. If the net benefit of gig work exceeds the net benefit of public program participation we might observe substitution away

from program participation when gig opportunities exist. Note, however, that the ability to self-insure through gig work operates through flexible labor market participation. If local economic conditions are poor, gig opportunities might be less beneficial as demand for gig services fall and the supply of gig-inclined workers rise. As such, gig work might prove an effective means of self-insurance in strong labor markets, but ineffective when the labor market is weak.

Based on this conceptual framework, we hypothesize several channels through which gig work may lead to reduced participation in social insurance programs. First, individuals facing negative income shocks—such as job loss, disability, or other idiosyncratic events—typically become eligible to participate in public assistance programs. These programs provide financial support but impose costs, including stigma, administrative burdens (Deshpande and Li, 2019), ordeal mechanisms (Nichols and Zeckhauser, 1982), and means-testing requirements. Because applying and maintaining eligibility for these programs is costly, individuals may instead choose to smooth income shocks through flexible, on-demand employment. Although gig work entails its own costs (e.g., foregone leisure or job-related expenses), if its net benefit exceeds that of program participation, we may observe substitution away from welfare.

Second, for individuals facing barriers to traditional employment—such as high fixed costs of labor force entry or constraints related to caregiving responsibilities (which are often associated with high labor supply elasticities; see Blundell and MaCurdy (1999))—gig work may provide a more accessible and flexible means of engaging in the labor market. By increasing labor supply and income through non-traditional employment, individuals can augment household income, potentially rendering them ineligible for means-tested benefits or leading them to voluntarily reduce reliance on public assistance. Although both of these channels are theoretically plausible, the extend that individuals substitute between gig work self-insurance and public social insurance is an empirical question.

Gig work, or the gig economy, is a term used to capture the novel set of non-traditional work arrangements, such as ride-share, food delivery, short term rentals, and pay-per-task

services (Abraham et al., 2018). These opportunities are usually characterized by online platforms and apps that connect consumers to contracted, predefined services that are short-term in nature. These positions are often framed as opportunities to engage in flexible, paid work. However, despite potential improvements in work flexibility and supplemental income, gig employment comes with trade-offs. These drawbacks range from low pay (Zipperer et al., 2022) and discomfort associated with semi-anonymous transactions involving complete strangers (Sundararajan, 2016), to economic vulnerability (Bergman and Jean, 2016; Zipperer et al., 2022) and a lack of non-wage benefits or legal protections such as minimum wages, overtime protection and paid leave benefits (Gale et al., 2018; Zipperer et al., 2022).

In the past 20 years there has been an explosion of gig work opportunities. Between 2013 and 2018, online platform gig work grew to approximately one percent of the overall workforce (Garin et al., 2022), with other sources reporting even higher estimates (Farrell et al., 2018). Census Bureau administrative data (Abraham, Haltiwanger, Hou, Sandusky and Spletzer, 2021; Abraham et al., 2019) and tax records (Garin et al., 2022) show a steady increase in self-employment from 2000 through about 2015, much of this attributable to gig work. This is particularly pronounced in the ride-share sector, where the number of nonemployer businesses in ground passenger transportation and taxi and limousine services grew by nearly 300 percent between 2010 and 2016 (Abraham, Haltiwanger, Hou, Sandusky and Spletzer, 2021; Abraham et al., 2019). The predominant source of gig work is ride-sharing. Farrell et al. (2018) use bank account data to show that nearly two thirds of households with income from online gig platforms have income from transportation platforms. For this reason, we will focus on the roll-out of ride-share to proxy for access to gig opportunities when estimating the trade off between social programs and gig employment opportunities.

2.1 The Roll-out of Uber

Although there are many ways to engage in gig work, the most common is through ride-sharing services like Uber and Lyft. During the mid 2000s, the number of nonemployer businesses in the ground passenger transportation sector nearly quadrupled (Abraham et al., 2019), with Uber being the largest ride sharing platform. Uber was established in 2009 and quickly spread across the United States, followed by Lyft, which was founded four year later. Uber maintains control over three quarters of the rideshare market, while Lyft controls most of the remaining quarter (Kaczmarski, 2024).[3]

Because of the timing, overall scope, and geographic spread of Uber, we view the roll-out of Uber as a proxy for overall access to gig work opportunities, not just ride share. This is justifiable for two reasons. First, Google search interest in Uber also precedes search interest in other gig platforms such as Lyft, TaskRabbit, Upwork, DoorDash, Aribnb, and Turo (see left panel of Figure 1). Second, using Google Trends search intensity to measure market entry, the geographic spread of other gig platforms moved similarly to the spread of Uber, but with a lag (see right panel of Figure 1). Local markets that Uber entered earlier were also entered earlier by other platforms. As such, we are not confident that we can solely isolate the effect of Uber access on program participation, but rather view Uber's entry as a proxy for the beginning of gig opportunities more broadly.

We use hand-collected data on Uber's roll-out that was constructed in conjunction with another project (Wilson, forthcoming). These data come from two main source: earlier roll-out data provided by Hall et al. (2018) and press releases on the Uber newsroom website. This measures when Uber began offering services in different cities that are then linked to Census Bureau core-based statistical areas or metropolitan areas (CBSAs). We then create two data sets. The first, is the metropolitan area-by-year level dataset which includes an indicator for whether or not Uber is operating in the CBSA in that year. The second is a county-level

[3]As Wilson (forthcoming) notes, Google Trends search interest in Uber is about 5 times higher than interest in Lyft.

dataset which crosswalks counties to metropolitan areas, and then applies the metropolitan level Uber entry measure to each applicable county. The roll-out was slow initially, only reaching seven metropolitan areas by the end of 2011 (Figure 2).[4] The widespread roll-out of Uber peaks in 2014 and 2015, reaching 161 additional metropolitan areas before slowing. Entry of Uber into a local market significantly increases Uber's penetration as captured by the number of drivers and Google Trends interest in Uber (Hall et al., 2018). Ride-share drivers are not a random sample of the population, they are more likely to be male, young, and unemployed than the full population.[5]

One concern is that the roll-out of Uber might be correlated with underlying trends that affect our outcomes of interest: social program participation. As Hall et al. (2018) suggest, the primary goal of Uber was to "cover as much of the nation (and world) as soon as possible." As such, Uber largely expanded to cities based on population, with population the strongest predictor of Uber entry timing (Hall et al., 2018). As seen in Table 1, although the counties that Uber entered earlier are more populous, they are quite similar along many other demographic and labor market dimensions. As discussed later, we adopt various empirical approaches that account for this form of selection and we examine pre-trends to verify that program participation is not trending differently in places Uber enters earlier.

3 Data

We use three datasets to paint a more complete picture of the effect of access to gig opportunities on participation in social programs. These data include administrative county caseload data, individual-level survey data, and individual-level administrative data. We describe each of the datasets here. These datasets are then merged to hand-collected data

[4]These CBSAs include San Francisco, San Jose, New York, Seattle, Chicago, Boston, Washington DC.

[5]As Wilson (forthcoming) notes, there are minimal barriers to driving for Uber. You must present an in-state driver's license that has been valid for at least one year (or three years if under age 25), you must have access to a four-door car, and you must pass an initial driving record and criminal history screening. It is not necessary that you personally own the vehicle, but if you do you must provide proof of insurance. Some states impose additional restrictions on things like the age or condition of the car. For many people the start up costs will be small.

on the roll-out of Uber across markets over time, which captures the variation in access to gig work that we exploit.

Administrative County Caseloads

We collected county-level enrollment and participation measures from various federal agencies that operate social programs, including data from the Social Security Administration (SSA), the US Census Bureau, and the United States Department of Agriculture (USDA) to construct a county-by-year panel of program participation from the early 2000s until 2020. With this data we can observe county-level enrollment in Supplemental Security Income (SSI), Social Security Disability Insurance (SSDI), and Supplemental Nutrition Assistance Program (SNAP, formerly food stamps). We obtain annual, county-level SSI and SSDI caseloads from the Social Security Administration (SSA) annual reports for each year from 2002 to 2020 for SSI and from 2004 to 2020 for SSDI. Data on SNAP enrollment is obtained from the USDA and spans 2002 to 2020. We then merged this dataset of program participation to county-level measures of employment, unemployment rates, and population obtained from the US Census Bureau Quarterly Census of Employment and Wages (QCEW), the Bureau of Labor Statistics (BLS) Local Area Unemployment Statistics, and the National Cancer Institutes' Surveillance, Epidemiology, and End Results Program which uses Census data to construct county-level population counts. These county-level characteristics are then merged to the county-level Uber roll-out data described above.[6]

We also collect annual, county-level measures of the number of non-employer establishments from the U.S. Census Bureau's Nonemployer Statistics program. These data capture the number of businesses without paid employees, including private contractors. Although not all gig workers are classified as non-employers, a substantial share fall into this category (Grundy and Alleyne, 2025). We construct the number of non-employer establishments in all

[6]Ideally, we would also examine county-level unemployment insurance caseloads.Unfortunately, these are only available at the state and national level. Individual-level data like the American Community Survey also do not separately identify unemployment insurance income.

industries, the transportation sector, passenger transportation specifically, and the service sector to examine whether access to gig work leads to significant changes in the number of non-employer businesses. Importantly, these measures do not capture all gig workers. The Nonemployer Statistics program explicitly excludes businesses with less than $1,000 in annual receipts. Previous work shows that the majority of individuals engage in gig work for a few months of the year and that median monthly earnings across platforms are below $1,000, and only about $100 for selling and non-transportation work (Farrell et al., 2018). Thus, our non-employer establishment counts are likely a lower bound on the prevalence of gig work. Given these distributional statistics, the true effects may be twice as large or more. For this reason, we do not interpret these measures as the "first stage" effect of gig work access on gig employment, but rather as suggestive evidence that individuals begin to adopt gig work when such opportunities become available.

American Community Survey

We use the American Community Survey (ACS) between 2005 and 2019 to explore the individual-level effect of gig work access on program participation because it allows us to estimate effects across several programs and provides a large sample with demographic characteristics, allowing us to explore heterogeneity. Using the ACS we construct an individual-level dataset, for adults 18 and older. We use self-reported income from social security and from supplemental security income to measure whether individuals participate in the program and how large their benefits are. Importantly, the social security income measure does not differentiate between social security old-age retirement payments and disability payments. However, we can also restrict the sample to individuals under retirement age to avoid capturing social security retirement payments. We use self-reported income from welfare to capture the extent to which families participate in cash transfer programs. The main federal cash transfer program is Temporary Aid for Needy Families (TANF) but other state or local transfers will also be included in this measure. We also observe whether or not

the family reported having food stamps or public insurance.

County identifiers are only available for people residing in highly populated counties, so we instead link each individual to their metropolitan area or if they are not in a metropolitan area to the state remainder. We then merge this to the metropolitan area Uber roll-out data described above and metropolitan area unemployment rates.[7] We use the provided survey weights in our estimation. Previous research has raised concerns about measurement error in program participation reports from surveys (Meyer and Mittag, 2019). This is why we examine both participation and amounts, but this is also why we use the Health and Retirement Study data, which can be linked to administrative program data for some programs.

Health and Retirement Study

We use RAND Health and Retirement Study longitudinal data from 1992 to 2020 linked to the restricted HRS geographic data file and the Social Security Administration's benefit records for HRS respondents. The Health and Retirement Study (HRS) data is a longitudinal study of health, retirement, and aging households with at least one respondent older than 50 years of age. HRS surveys a representative sample of approximately 20,000 people in the United States over time, supported by the National Institute on Aging and the SSA, and collects comprehensive information on income, asset, employment, retirement, and pension plans, and retirement and Social Security benefits. We utilize the harmonized longitudinal HRS created by RAND Corporation (RAND-HRS data hereafter) to create a clean cross-wave sample of analysis. The RAND-HRS data are matched with the SSA data on benefits. SSA administrative data contains retirement, disability, and additional income benefits for HRS respondents who agreed to disclose their information. It also allows us to access program application and award to fully capture the source of the effects on Social Security Programs

[7]These unemployment rates include the unemployment rate for the non-metro state remainder. We construct this by subtracting the number of unemployed and the number in the labor force in metro areas in the state from the state total and then construct the state remainder unemployment rate.

participation. Since SSA data contains records on annual program participation and benefits while HRS data is fielded in even years, we fill in information for RAND-HRS data in odd years.[8] The matched HRS-SSA data resulted in roughly 185,000 observations between 1992 and 2020 in the analytic sample.[9] The matched SSA-HRS data then is linked to geographic files to obtain county-level place of residency, which is used to define our treatment status. All monetary values are expressed as real 2019 dollars. Finally, we merge the data to county-level unemployment rates. In some specifications we add state-level controls, including state median income from Census data; state housing prices (from Federal Housing Finance Agency (FHFA) House Price Index); state unemployment rate (from Local Area Unemployment Statistics – US Bureau of Labor Statistics); state gross products and the number of AFDC/TANF recipients from National Welfare data (Center for Poverty Research, University of Kentucky).

4 Empirical Approach

We employ difference-in-differences strategies to identify the effect of gig opportunity access on the number of non-employer establishments and program participation. As noted above, Uber rolled-out across cities often starting with the biggest cities in terms of population, but not necessarily for reasons associated with social program participation. To the extend that local population is fairly stable over the sample period, our difference-in-differences estimate will account for differences in population levels or other fixed characteristics that might affect the timing of Uber entry and the outcomes of interest. For this reason we restrict the analysis to counties and individuals in metropolitan areas, that are similar in terms of population. We will also make comparison between early- and late-Uber adopting areas, which are more similar and evaluate event studies to ensure that Uber-adopting cities do

[8]For time-invariant variables such as gender, races, education, we keep the same information between 2 consecutive years. For time-variant variables such as marriage, sources of income, home ownership, we use the median values to fill in information for odd years.

[9]that we excluded those who were interviewed in 2021 afterward to exclude the Covid-19 pandemic period.

not follow different trends from cities that adopt later or never. We leverage the differential timing of Uber deployment in different cities as plausibly exogenous treatment that increased the gig employment opportunities. We will estimate these effects using several methods at several different units of observation. First, we will estimate the standard two-way fixed effects regressions. For the county-level caseloads we estimate the following regression

$$CaseRate_{ct} = \theta_c + \lambda_{st} + \beta UberOperating_{cst} + \gamma Urate_{ct} + \varepsilon_{cst} \tag{1}$$

The outcome of interest is the number of cases per 100 individuals in the given social program in county c in state s in year t. We examine disability insurance, supplemental security insurance, and SNAP participation rates in the county-level data. We also document the effects on the number of non-employer establishments per 100 working age adults (18-64) to determine if gig work access affects the prevelance of gig employment. We include county fixed effects to control for fixed differences in program participation across counties. This also accounts for things like county population that could differ between treatment and control counties over the sample period. We also include state-by-year fixed effects to make this a comparison between counties in the same state. These fixed effects will control for differential trends in program participation across states and compare counties that face the same state-level policy structure. Our coefficient of interest is β which captures the effect of having Uber currently operating in the county on caseloads. We also control for the annual, county-level de-meaned unemployment rate ($Urate$) to control for local economic conditions. We adjust the standard errors for clustering at the metropolitan area as this is the level at which Uber rolled out and treatment was assigned.

With this estimation, our identifying assumption is that counties where Uber rolled out would have evolved like other counties in the same state that Uber had not yet entered. As counties in the same state face the same policy regimes, this seems plausible. We also explore pre-trends to see if treated and untreated counties evolve similarly. As seen in Table 1, there are level differences between counties where Uber has not entered by 2019 and

counties that Uber entered between 2010 and 2019. However, as seen in columns (1) and (2) of Table 1, counties that adopted Uber earlier and later are more similar. Early- and late-adopting counties in the same state only differ significantly across a few dimensions. Although Uber's decision to expand into a metropolitan area might not be exogenous, it is plausible that the timing of expansion is exogenous to local characteristics that might affect program participation, conditional on population. For this reason we also estimate results on the sample of counties that adopt by 2014 and compare outcomes between early Uber entry counties and later Uber entry counties. This results in a weaker identifying assumption and is consistent with methods used to evaluate the impacts of Uber in other contexts (Gentry, 2025; Wilson, forthcoming).

Not only do we want to see if access to Uber affects program participation, we want to determine the extent to which flexible gig work and program participation provide substitute forms of insurance against shocks and if there is crowd out. To do this we augment equation (1) with an interaction term as follows:

$$CaseRate_{ct} = \theta_c + \lambda_{st} + \beta UberOperating_{cst} + \gamma Urate_{ct} + \delta UberOperating_{cst} * Urate_{ct} + \varepsilon_{cst} \quad (2)$$

The δ coefficient provides an estimate of how Uber access changes program participation as the unemployment rate rises. This will allow us to determine if the substitution away from social programs when Uber is available increases or decreases as the unemployment rate rises. A positive δ would suggest that substitution away from public programs is even stronger in poor economic conditions. A negative δ would indicate that the degree of substitution is offset or mitigated when the labor market is weak. Since $Urate$ is de-meaned, the interpretation of β now changes to represent the total effect of Uber operating when the unemployment rate is at the mean.

Recent work has shown that two-way fixed effects (TWFE) regressions with staggered treatment timing might not uncover the causal effect of treatment because of the implicit weighting in the TWFE and potential dynamic effects (Callaway and Sant'Anna, 2020; de Chaisemartin and D'Haultfœuille, 2020; Goodman-Bacon, 2020). For this reason, we augment our TWFE analysis using an approach robust to staggered treatment timing. We estimate event-study style treatment effects using the doubly robust difference in differences estimator proposed by Callaway and Sant'Anna (2020), namely CSDiD estimates. Many of the proposed methods rely on units that remain untreated at the end of the sample period to serve as counterfactuals for treated units. As seen in Table 1, it is clear that counties where Uber has not entered by 2019 differ from counties that Uber entered between 2010 and 2019. As such, it is possible that these counties do not provide an accurate counterfactual for what would have happened in Uber expansion counties if Uber had not expanded. For this reason we also estimate county-level specifications comparing counties that adopted Uber earlier to those that adopt later.

Importantly, the CSDiD estimator does not permit models that interact multiple treatments, especially when one treatment is continuous, such as local unemployment rates. For this reason we focus on the TWFE model results, so we can examine how gig work opportunities interact with local economic conditions in shaping welfare program participation, but show that our baseline estimates are robust to these innovative approaches.

When using the ACS and HRS we estimate similar specifications, but at the individual level as follows:

$$Participate_{ict} = \theta_m + \lambda_{st} + \beta UberOperating_{mst} + \gamma Urate_{mt} + \varepsilon_{ist} \tag{3}$$

and

$$Participate_{ict} = \theta_m + \lambda_{st} + \beta UberOperating_{mst} + \gamma Urate_{mt} + \delta UberOperating_{mst} * Urate_{mt} + \varepsilon_{ist} \quad (4)$$

In the ACS analysis *UberOperating* and *Urate* are assigned at the metropolitan area (CBSA) level, because county is not available for everyone in the sample. In constrast, in HRS analysis, we are able to evaluate the data at the county-level. Therefore, we assign the treatment when Uber entered at the CBSA-level for ACS data and at the county-level for HRS data. For most of our analysis we estimate reduced form effects, as there is no clear consensus on how to identify gig workers in government surveys or caseload data (United States Government Accountability Office, 2017), and the Non-employer Statistics likely miss many gig workers. However, the ACS and HRS do allow us to explore individual-level heterogeneity and determine which groups' program participation are most sensitive to gig opportunities.

5 Results

5.1 Effects on the Prevalence of Gig Workers

We begin by presenting results documenting the effects of gig work access on the prevalence of non-employer establishments, which include a subset of gig workers, in Table 2. When Uber begins operating in a CBSA, the total number of non-employer establishments per 100 working-age adults increases by 0.259. More than half of this increase is driven by the transportation sector, and passenger transportation specifically, consistent with the expansion of Uber services. However, the roll-out of Uber also increases the number of non-employer businesses in the service sector, consistent with Uber's entry proxying for broader access to gig opportunities. Estimates are similar when we include the interaction between Uber ac-

cess and unemployment rates, though negative and significant coefficient on the interaction term indicates that fewer individuals pursue gig work when the labor market conditions are weaker.

As noted above, the non-employer establishment data likely under-count gig workers as only establishments with annual receipts exceeding $1,000 are included. Similarly, individual contractors who earn small amounts do not face mandated third party reporting (Garin et al., 2022) and therefore are not required to file self-employment tax returns. These estimates should thus be interpreted as a lower bound on the effect of gig work access. Based on previous work documenting the earnings of gig workers and the number of months worked (Farrell et al., 2018), the total effects could be at least twice as large. As such, we do not use these estimates as a "first stage" to establish a local average treatment effect, but rather as evidence that Uber's entry affected the prevalence of gig work.

We also provide doubly robust event-study estimates on the number of non-employer establishments in Figure 4. We observe flat pre-trends, followed by rapid post-entry growth, resulting in an increase of approximately 0.5 non-employer establishments per 100 working-age adults eight years out. Taken all together, these findings indicate that the roll-out of Uber leads to significant gains in the prevalence of gig work.

5.2 County-Level Results

Now, we present results on county-level program caseloads from equations (1) and (2) in Table 3. When Uber is operating in the CBSA the SSDI cases fall by 0.17 people per 100 residents, or 3.3 percent off of a base rate of 5.16 recipients per 100 residents. We see a significant drop in SSI enrollment rates among 18-64 year olds, with rates dropping by 0.067 people per 100 residents (2.6 percent). There is also a larger decline of 0.68 SNAP recipients per 100 residents (5.4 percent).[10] These results suggest that when there is increased access to gig opportunities fewer people participate in social insurance and transfer programs. The

[10]Effects on SNAP participation might be larger as it includes children and other family members, not just the individual.

SSDI and SSI estimates are about a quarter to half as large as our estimated effects on the number of non-employer establishments, but this does not provide appropriate scaling as the non-employer establishment data misses many gig workers. Previous estimates suggest that 1-2 percent of the annual workforce was employed in gig work (Farrell et al., 2018; Garin et al., 2022), if not substantially more (Gallup, 2018; United States Government Accountability Office, 2017). This would suggest that at most, for every 10 new gig workers, approximately 1 to 2 do not collect disability insurance, less than one does not collect SSI, and between 3.5 and 7 do not participate in SNAP. This represents an economically significant substitution between formal social insurance and gig employment.[11]

We next interact the presence of Uber with the local, demeaned unemployment rate. At the average unemployment rate, access to gig opportunities reduces SSDI, SSI, and SNAP participation at approximately the same rate as in the previous specification. However, the rate of substitution falls as the unemployment rate rises. For all three programs the reduction in caseloads associated with Uber goes to zero when the unemployment rate is about two percentage points above the mean. When examining county-level caseloads there is a trade-off between gig opportunities and program participation, but that trade-off is ameliorated as local economic conditions get worse. In tight labor markets with gig opportunities individuals rely less on social insurance programs, but as local economic conditions get worse, they rely more on public programs and less on private self-insurance through gig work.

5.3 Robustness

In Table A2 we explore the robustness of the county-level results to various sample and specification changes. If we weight by the county population at the beginning of the sample in 2002 the SSDI and SSI estimates are larger, while the effects on SNAP are smaller, but still significant. Results are also similar if we include state and year effects separately rather than state-by-year. As seen in Table 1, places that ever adopted Uber are more similar in terms

[11] We cannot differentiate if the lower rates of participation are due to falling inflows as people choose alternatives to social programs or increased outflow and exit from the programs.

of demographic characteristics. Effects are similarly significant, but smaller in magnitude if we limit the sample to counties where Uber had entered by 2014 to isolate variation in the timing of roll-out. Results are also robust to excluding counties that adopted Uber in 2010, the first year of Uber. Finally, as noted above, total population was one of the strongest predictors of Uber's entry Hall et al. (2020). Results are not changed significantly if we control for population, or when we add additional county-by-year level controls like race shares, gender shares, age bin shares (under 18, 18-30, 31-54, 55-64, and over 64), one digit industry shares, and the median home value.[12]

5.4 Staggered Treatment Timing Corrections

Our results are also robust to doubly robust methods that account for staggered treatment timing (Callaway and Sant'Anna, 2020; de Chaisemartin and D'Haultfœuille, 2020; Goodman-Bacon, 2020). Event studies are provided in Figure 5. We see that pre-trends are flat, but after the introduction of Uber county-level enrollment in SSDI, SSI (among those under 64) and SNAP all decline. The declines in SSDI and SSI are statistically significant, while the much larger declines in SNAP are not. We also provide county-level CSDiD estimates comparing treated counties where Uber has entered to counties that will be treated in the future in Figure A1 and find similar results. These doubly robust difference-in-differences estimators provide consistent evidence that access to gig opportunities through Uber are associated with significant decreases in SSDI and SSI participation rates.

We also find similar evidence when using a stacked panel approach similar to that used by Deshpande and Li (2019) and Gentry (2025) and recommended by Goodman-Bacon (2020). First we identify all counties that Uber entered in a given year. We then match this will all counties that Uber entered exactly four years later, creating a dataset where we can compare the effect of treatment relative to similar counties that receive treatment four years later. We then stack each of these datasets to estimate the average effect of treatment relative to

[12]Estimates from the ACS and HRS are also similar when we control for population.

counties that were treated exactly four years later. As seen in Table A1 the point estimates are similar in magnitude and not statistically different when using the smaller stacked panel. The implications are the same. Access to Uber reduces program participation in SSDI, SSI, and SNAP, but this reduction is ameliorated as local economic conditions become worse.

We also provide event study evidence based on the stacked panel in Figure A2. These event studies compare county-level caseloads per 100 residents in counties where Uber entered relative to counties that Uber entered four years later. During the five years before Uber entered trends are flat, consistent with early and late Uber-entry counties following similar trends in program participation. However, consistent with the evidence in Tables 3 and A1 caseloads in SSDI and SNAP fall significantly and stay lower by about -0.1 cases (for SSDI) and -1 case (for SNAP) for the next three years after Uber's entry. We see a similar patter in SSI caseloads, although the decrease is smaller.

5.5 Individual-Level Results

We next explore individual-level effects of gig work access on program participation using ACS and HRS data. This will allow us to explore different outcomes and heterogeneity by person characteristics. Because the ACS is a repeated cross-section, the individual-level analysis is not as conducive to the CSDiD methods or the stacked county-level analysis. Similarly, the small matched HRS-SSA sample is not as conducive to the staggered timing methods. For this reason we focus on the two way fixed effects estimation at the individual level, with staggered treatment corrections in the appendix. However, given the similarity between the county-level two way fixed effects and corrected estimates, the individual level two way fixed effects are still informative.

Results from ACS data

We present the individual-level ACS results in Table 4. In order to compare these effects to the county-level effects we multiply the binary outcomes by 100, so we can interpret them

as effects per 100 residents. In the ACS sample, we restrict the sample to adults 18-60, so we can differentiate social security old-age income from disability income. We find effects on having social security income (which will mostly be disability insurance for this population) that are similar in magnitude to the effects at the county-level. Access to gig work reduces the probability of receiving SSA income by 0.12 percentage points, or by 0.12 recipients per 100 residents. Unlike the county-level estimates, this elasticity does not change with local economic circumstances. This might be due to differences in what individuals perceive as social security payments, differences between county and metropolitan area unemployment, or differences in the sample years. In the individual-level data we find that Uber's entry also reduces SSI receipt, but the estimated effects are larger than the county-level estimates. We observe a similar pattern, where the substitution between gig opportunities and SSI participation is damped in places with higher unemployment rates.

We see no changes in welfare income (e.g., TANF or other state and local programs) and effects on SNAP receipt that are similar to, but smaller than the county-level estimates. We find some evidence of reductions in public insurance use. We mostly see the same pattern of substitution between Uber and programs falling as the unemployment rate rises, although it is not present for SSA income receipt. Overall, these results are consistent with the county-level caseload analysis, suggesting that individuals substitute away from social insurance and safety net programs when flexible gig opportunities are available, but this tradeoff is dampened when local economic conditions get worse.

In Table 5 we look at the amount of income individuals have from the Social Security Administration, from Supplemental Security Income, and from welfare payments.[13] Access to gig opportunities, as proxied by availability of Uber, is associated with a $18.89 reduction in annual SSA income and a $15.30 reduction in annual SSI income. Once again, these represent intent to treat estimates. The effect on transfer dollars weakly declines as local economic conditions deteriorate.

[13]Income amounts for SNAP and public insurance are not reported in the ACS.

The ACS individual-level data also allows us to document heterogeneous effects across different demographic groups (Figure A3). Consistent with demographic patterns in safety-net program use, the substitution away from SSDI when gig opportunities are available are largely driven by less-educated, older, single, and non-Hispanic White individuals. The reductions in SSI participation are much more broad-based, with nearly every group observing a significant reduction in SSI participation. We do not detect statistically significant differences in SNAP, or welfare participation across the different demographic groups. We also estimate effects for non-disabled individuals and show that the reductions in program participation are apparent for these groups as well, not just the disabled (Gentry, 2025).

Results from HRS data

Table 6 uses the matched HRS-SSA data and reports estimates from equations (3) and (4) for participation in Social Security programs (SSDI and SSI). Consistent with previous results, we find a significant decline in both program application and receipt following Uber's entry. For instance, access to gig opportunities is associated with a 2.6 percentage point (or 11 percent) reduction in the probability of SSDI application and a 2.2 percentage point (or 20 percent) reduction in SSDI receipt (see Columns 1 and 3, Table 6).[14] The larger effects observed in the HRS data, compared to those in the county-level data and the ACS data, is due to the fact that we draw the sample of analysis from the SSA's records linked to the HRS data, which essentially contained individuals who either applied for or are eligible for Social Security benefits. Despite concerns about mismeasurement of program participation (Meyer and Mittag, 2019), we find similar results using the administrative data.

When accounting for local economic conditions, we observe slightly diminishing effects of Uber entry in counties with higher unemployment rates. As shown in Column 2, in counties with tighter labor markets, Uber's entry has a more pronounced negative effect on SSDI claims. In contrast, in areas with higher unemployment, the effect is possibly attenuated

[14]This larger reduction in SSDI uptake aligns with Rutledge et al. (2018), who find that contingent workers are less likely to apply for SSDI benefits.

because individuals in these areas face more barriers to entering the gig economy or because demand for gig-based services such as food delivery and ridesharing is weaker.

For SSI outcomes, we observe a similar pattern. Access to gig opportunities like Uber is associated with a 3.4 percentage point (or 17.7 percent) reduction in the probability of applying for SSI (see Column 5). While the average effect on SSI receipt is not statistically significant (Column 7), the interaction model (Column 8) suggests that in counties with stronger local economies, SSI receipt falls by 0.3 percentage points, indicating that gig work may serve as a substitute for welfare participation in such settings.

Appendix Table A3 presents the results for the participation in other welfare programs, where we find similar patterns.[15] For example, food assistance receipt declines by 1.3 percentage points among older adults in counties where Uber has entered (Column 1), with stronger effects observed in areas with lower unemployment rates. Effects on the number of benefit dollars are negative, but statistically insignificant (Appendix Table A4).

As noted above, the CSDiD and stacked event study methods to account for staggered treatment timing are less appropriate for the ACS and HRS. Because the ACS is cross-sectional, we cannot follow individuals over time or across locations. Hence, we aggregate the ACS data at the CBSA-year level and perform similar analyses as those using county-level data. Using the ACS microdata, collapsed to the CBSA-by-year level, we see noisy, but consistent patterns (Figure A4). For the HRS data, the sample of matched HRS-SSA respondents is relatively small, limiting our ability to distinguish between early and late adopters. Therefore, we use the CSDiD estimator by comparing treated counties to "never-treated" counties within the HRS sample. These estimates are presented in Figures 6 and A5. In the HRS, we find consistent reductions in SSDI claims, benefit receipt, and income. However, for SSI we only find significant declines in claims. This pattern may indicate that more marginal applications are no longer being filed, or that the additional income from

[15]Note that Food Stamp, Medicaid, and other welfare outcomes are derived from self-reported in the HRS data which is only available on even years. Therefore, the number of observations is half that for the SSDI and SSI outcomes which come from the SSA data

gig work reduces SSI eligibility among older individuals. Across all specifications, we find no evidence of differential pre-trends between treated and comparison groups; pre-treatment coefficients are flat and statistically indistinguishable from zero. These results strenghten the validity of our TWFE estimates.[16]

5.6 Effects on Labor Market Outcomes

Taken together, these findings support a "labor substitution" hypothesis: when Uber enters a market with relatively strong labor market conditions, more individuals appear to opt for gig work over traditional welfare benefits, consistent with public program participation inducing administrative burden and stigma costs that individuals would prefer to avoid. Another benefit of the individual-level analysis is the ability to estimate how access to gig opportunities affects labor market outcomes and total income.

Using both the ACS and the HRS we estimate how having Uber in the local market affects employment, self-employment, and various measures of income (Tables 7 and A10). Having Uber in the labor market increases the probability of employment by 0.6 percentage points. As seen in column (2), the effect is larger in places with tighter local labor markets, but shrinks when the unemployment rate rises consistent with the substitution patterns seen above. We see smaller increases in self-employment, but this is in part because this only references the primary job and many survey participants do not classify gig employment as self-employment (Abraham, Haltiwanger, Hou, Sandusky and Spletzer, 2021; Abraham et al., 2019). Access to Uber does not affect income (total, wage, or family income) on average, but we do find that income increases when Uber enters the market, if the local labor market is strong (at or below the mean unemployment rate). However, as the unemployment rate rises these gains are eroded. At the mean unemployment rate, access to gig opportunities increase individual income by 519 to 689 dollars and family income by about twice that much. This represents economically significant income gains. These increases in income are larger than

[16]To the extent possible we also explore heterogeneous effects by sub-populations in the HRS data but because of the smaller sample size do not find meaningful, statistically significant differences.

the declines in programmatic income, suggesting a net increase in income. Consistent with local economic conditions mediating the substitution between gig work self-insurance and public social insurance, we find that incomes only rise when the labor market is strong. This further suggests that self-insuring through gig work is less effective at insuring against aggregate, macroeconomic shocks and for many is not beneficial if the labor market is poor.

6 Discussion

The rise of the gig economy has significantly transformed the labor market over the past two decades (Garin et al., 2023; Jain, 2024; Katz and Krueger, 2019). Platforms such as Uber, DoorDash, TaskRabbit, and Upwork have lowered barriers to entry and facilitated access to temporary, flexible work in a way that enables individuals to generate income with minimal credentialing or long-term commitment.

Despite this rapid change in the labor market landscape, our understanding of how individuals rely on gig work as a safety net, and how it interacts with traditional safety net programs remains underdeveloped. In this study, we examine how increased access to gig opportunities - proxied by Uber's entry into local economies - affects participation in welfare programs and individual income. We draw on three complementary datasets: county-level administrative data on benefit receipt, the American Community Survey, and the Health and Retirement Study linked to administrative Social Security Benefits data. We implement a difference-in-differences approach to estimate the impact of Uber's market entry on program participation.

Our findings indicate that Uber's penetration is associated with statistically significant reductions in participation across multiple welfare programs, including SSDI, SSI, and SNAP. Gaining access to gig work leads to reductions in social insurance program caseloads like SSDI and SSI by 2 to 3 percent. The reductions in SNAP participation are even larger, at approximately 5 percent. These results are robust across datasets and alternative staggered-treatment timing approaches. The evidence suggests that access to gig opportunities can

act as a form of informal insurance and income supplementation that reduces reliance on public assistance. Furthermore, it indicates that gig work may serve as a flexible economic buffer, enabling individuals to respond quickly to financial need without resorting to long-term government support. In other words, access to gig opportunities provides a new way for individuals to self-insure and crowd out public insurance.

Applying our estimates to the national population suggests that the aggregate fiscal impacts of substitution away from social insurance and toward supplemental gig-based self-insurance are potentially substantial. The county-level caseload estimates and the individual-level participation estimates imply that access to gig work reduces SSDI participation rates by 0.123-0.167 participants per 100 residents and reduces SSI participation rates by 0.067-0.171 participants per 100 residents. If we apply this to the working-age population in counties that adopted Uber during our sample window, we estimate that between 159,000-257,000 fewer people participate in SSDI and between 103,000-222,000 fewer people participate in SSI by 2019.[17] This represents an approximately 2.5 percent reduction in caseloads. This is a potentially large source of government savings. Using the benefit amount estimates obtained from the ACS, we estimate that the expansion of Uber reduced aggregate annual SSDI benefit outlays by approximately $2.43 billion, and reduced aggregate annual SSI outlays by nearly $1.97 billion by 2019. Relative to total SSDI benefits of $145.05 billion (Social Security Administration, Office of the Chief Actuary, 2024) and SSI federal benefits of $53.29 billion (Social Security Administration, Office of Retirement and Disability Policy and Office of Research, Evaluation, and Statistics, 2020) in 2019, this represents a 1.7 percent and 3.7 percent drop in annual SSDI and SSI payments respectively. These findings underscore the potential for flexible work arrangements to lessen dependence on public programs and reduce government expenditures.

Private market provision of gig opportunities like Uber lowers short-run costs for the government. This is evidenced by both the observed decline in reported benefits and recipient

[17]For reference, previous work suggests that there are several million gig workers in the US.

rates. Within a marginal value of public funds framework (Hendren and Sprung-Keyser, 2020), this implies a negative net fiscal cost, suggesting an infinite marginal value of gig opportunity provision. However, the substitution between gig work and public assistance is sensitive to local economic conditions. The willingness to pay among recipients - measured by the increase in income associated with gig work access in the ACS data - is only positive when labor market conditions are favorable.[18] In a weaker labor market, gig opportunities do not provide a sustainable means of income insurance, leading to an average short-run willingness to pay that is statistically indistinguishable from zero.

These findings imply that society cannot rely on the gig economy to fully substitute for the insurance function of social programs. The effect of Uber entry on program participation weakens during periods of high unemployment, suggesting that gig platforms cannot substitute for comprehensive safety nets during systemic economic downturns. Although gig opportunities appear to be a viable option to privately insure when labor markets are strong, this appears to be less feasible when more people are looking for work, as evidenced by an increased reliance on safety net programs. Our estimated effects on income provide consistent evidence that individuals only experience higher income from gig work access when the labor market is relatively stronger. When labor markets are weak, there is potentially less demand for gig work and more supply of people willing to engage in gig work, reducing earnings. This diminished insurance value during recessions highlights the continuing importance of social insurance programs as automatic stabilizers that protect households against systemic macroeconomic shocks.

Although the provision of gig opportunities is cost effective in the short-run, the long-run, dynamic consequences of substitution away from public programs into gig work are ambiguous. Gig workers, often classified as independent contractors, are responsible for both the employer and employee portions of payroll taxes. Yet, underreporting of income is common, which in turn reduces contributions to Social Security and leads to lower future

[18]For older workers in the HRS, the income effects are more positive, suggesting a positive willingness to pay for some subgroups.

retirement benefits. The nature of gig work also poses challenges for eligibility under existing employment-based social safety net programs, such as Unemployment Insurance and Social Security Disability Insurance, where eligibility is a function of formal employment histories. Over time, as these workers age, the lack of employer-sponsored retirement vehicles and consistent contributions places them at greater risk of economic insecurity in later life. Increased reliance on gig work as self-insurance could exacerbate retirement savings inequality and impose additional burdens on public support systems later. In a marginal value of public funds framework, this makes the long-run willingness to pay and government net costs less clear, and something that should be studied further once more time has passed and data become available.

Our findings have important policy implications. First, they show that in the evolving economy, alternative methods of self-insurance now exist that have potential implications for the amount of crowd-out and efficiency introduced by social insurance programs. Second, they caution against overestimating the capacity of the gig economy to reduce demand for traditional welfare programs, particularly in times of aggregate economic distress. While gig employment may serve as a supplemental income source for some workers, they do not offer the security, stability, or institutional supports necessary when there are widespread economics downturns. Our results emphasize the continued necessity of strong public safety-net programs, particularly during economic downturns when alternative self-insurance mechanisms may not be accessible or sufficient. Finally taken together, our work highlights the value that could come from adjusting policy to better accommodate gig work and workers who increasingly operate outside of standard employment arrangements.

Disclosure: During the preparation of this work the authors used ChatGPT to write the abstract. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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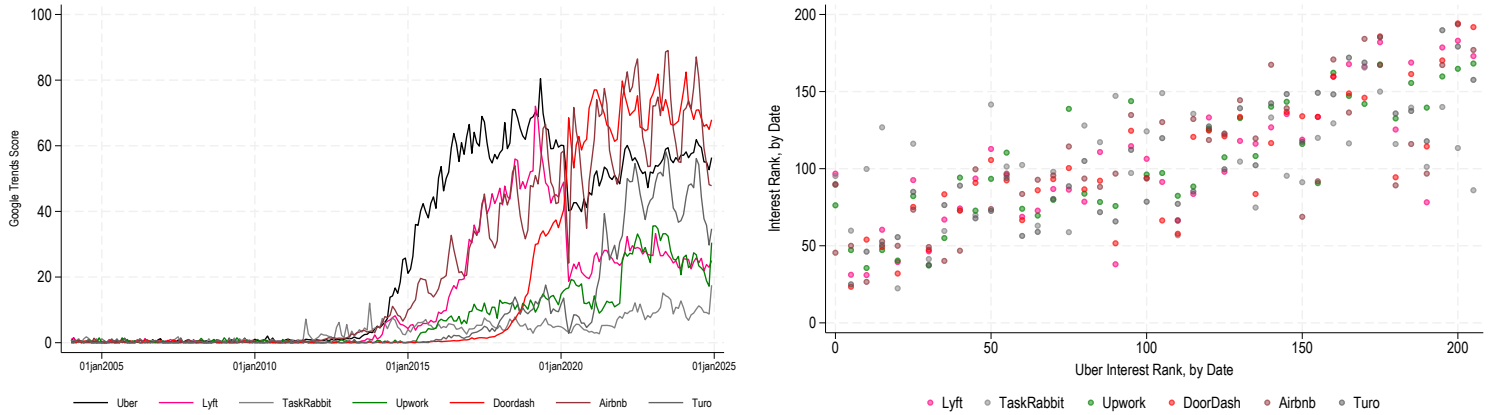
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Tables and Figures

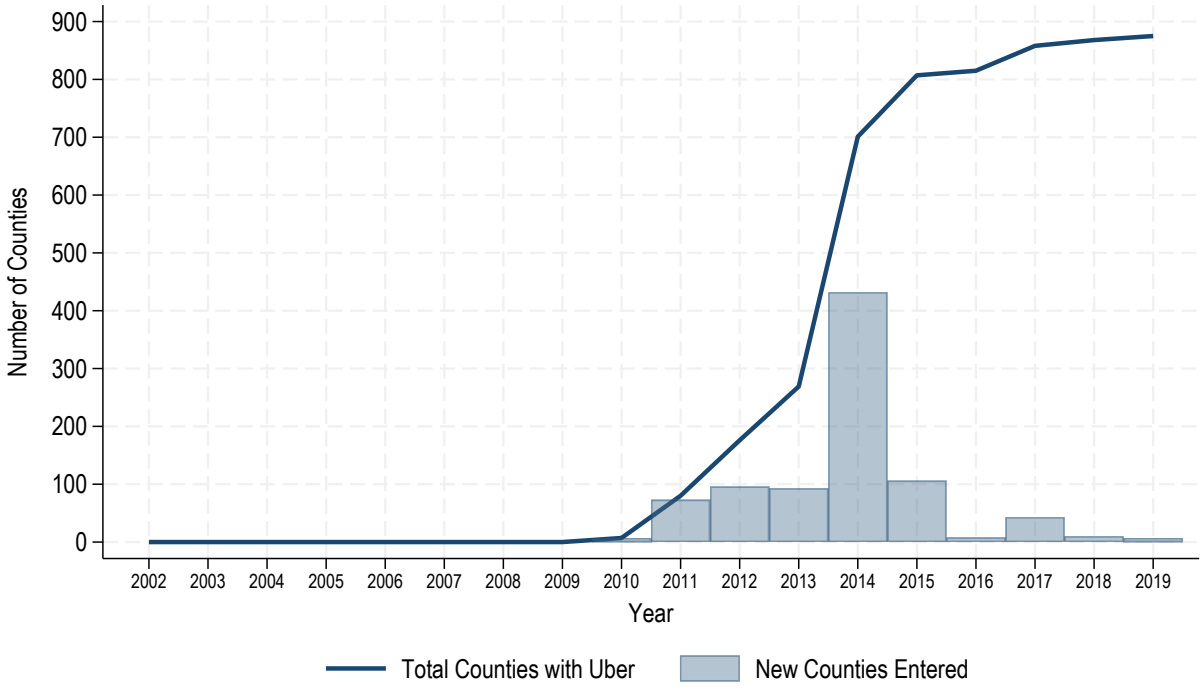
Figure 1: Roll-out of Uber Pre-dates and Predicts Other Gig Platform Roll-out Across Geography and Time



NOTE: In the panel on the left the average monthly search interest across Designated Market Areas (DMA, similar to CBSAs) for gig related companies such as Uber, Lyft, TaskRabbit, DoorDash, Airbnb, and Turo is plotted. The Google Trends data measures the relative search interest for a given term within a geographic region over time. This search interest is then normalized within geography so that the maximum search interest takes a value of 100 and every other date is measured relative to that. In the right panel we identify the first time the 6-month rolling average of search interest for each platform exceeds 25. This allows me to identify when search interest across the terms starts to rise, consistent with growth and expansion. We then plot the relationship between the ranking of Uber interest (in terms of earliest to latest) on the x-axis and the ranking of other terms on the y-axis. We plot this as a bin scatter with the average ranking of the other terms in ranking bins of 5. Markets that became interested in Uber earlier also tend to become interested in the other gig platforms earlier.

SOURCE: Reproduced from (Wilson, forthcoming) based on data from Google Trends.

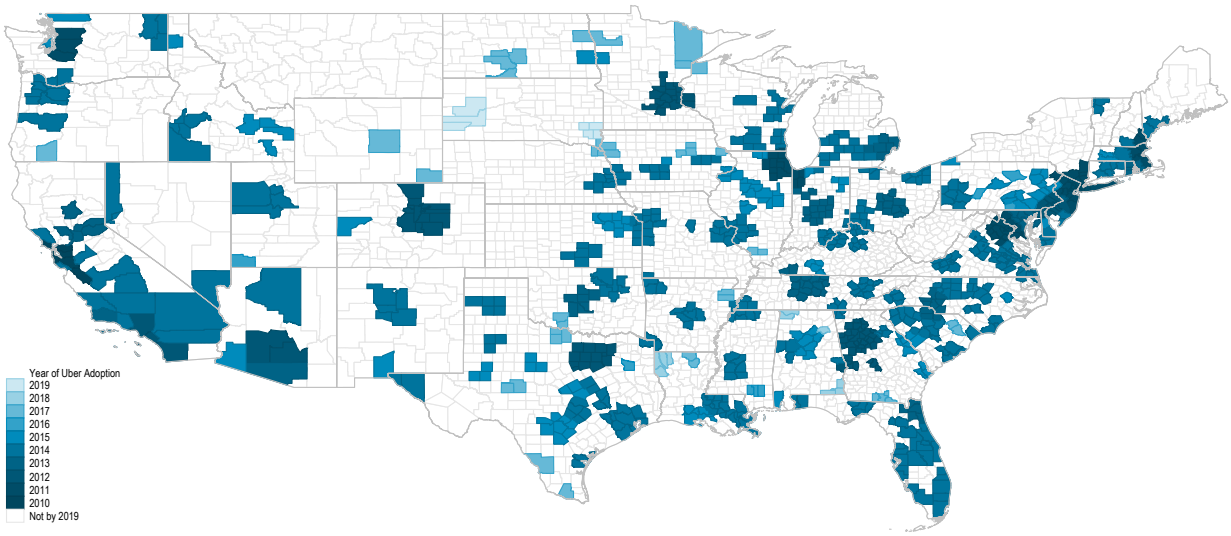
Figure 2: Roll-out of Uber Across Time



NOTE: Counties plotted by the year Uber began operating in the metropolitan area. This is assigned to counties using a CBSA to county crosswalk.

SOURCE: Authors' own calculations using self-collected data and data from Hall et al. (2018) on Uber availability.

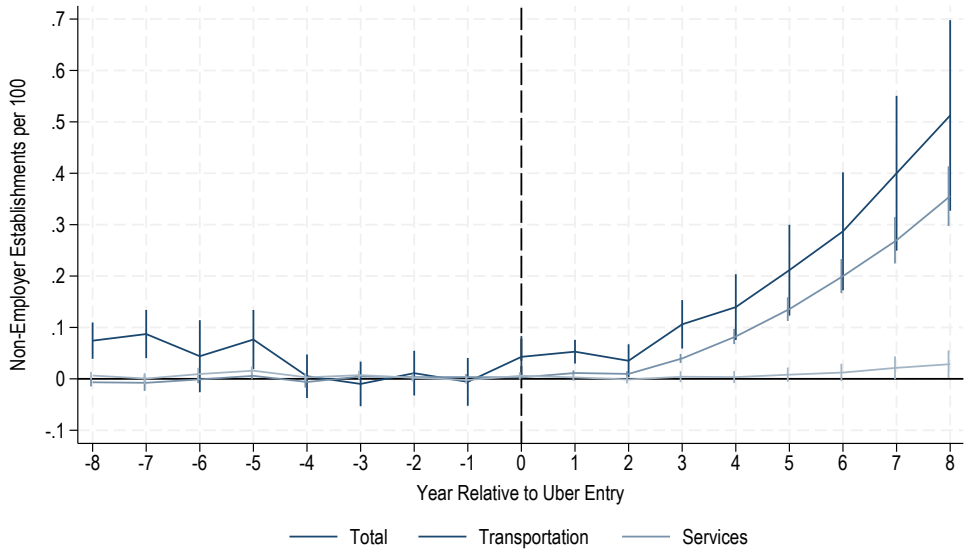
Figure 3: Roll-out of Uber Across Counties



NOTE: The year Uber began operating in the metropolitan area is provided. This is then assigned to counties using a CBSA to county crosswalk.

SOURCE: Authors' own calculations using self-collected data and data from Hall et al. (2018) on Uber availability.

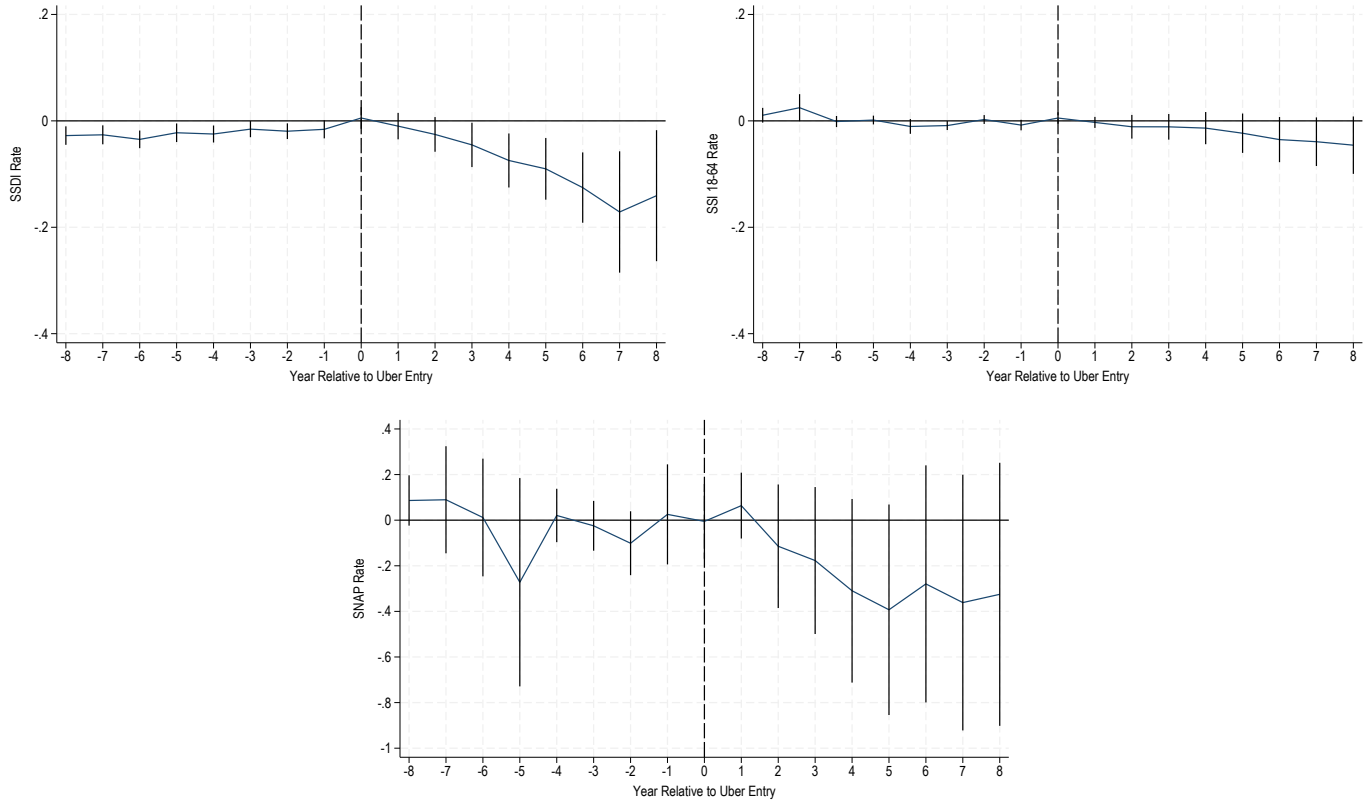
Figure 4: Doubly Robust Staggered-Timing Corrected Event Study Effects of Uber Entry on Prevalence of Gig Work



NOTE: Estimates obtained using doubly robust CSDiD difference in difference event study methods, as proposed by Callaway and Sant'Anna (2020). Treated counties are compared to counties that are never treated. Only counties in CBSAs are included. Standard errors are clustered at the metropolitan area level, with 95-percent confidence intervals displayed.

SOURCE: Authors' own calculations using the county-level nonemployer statistics.

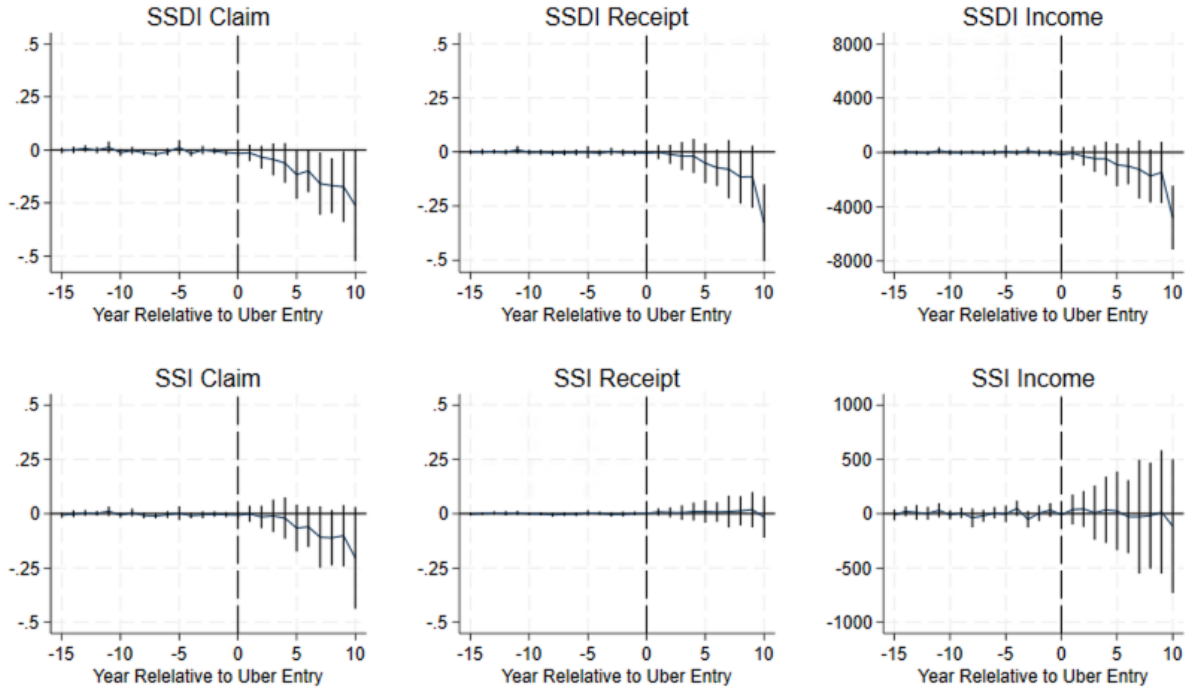
Figure 5: Doubly Robust Staggered-Timing Corrected Event Study Effects of Uber Entry on Program Caseloads



NOTE: Estimates obtained using doubly robust CSDiD difference in difference event study methods, as proposed by Callaway and Sant'Anna (2020). Treated counties are compared to counties that are never treated. Only counties in CBSAs are included. Standard errors are clustered at the metropolitan area level, with 95-percent confidence intervals displayed.

SOURCE: Authors' own calculations using the county-level panel.

Figure 6: Doubly Robust Staggered-Timing Corrected Event Study Effects of Uber Entry on SSA Programs in HRS



NOTE: Estimates obtained using CSDiD models. Data come from matched SSA-HRS data from 1992 to 2020. Sample includes working individuals aged younger than 70. All models include demographic control (age, marital status, gender, education, race/ethnicity, family size, immigrant status, veteran status, and self-reported health condition. 95-percent confidence intervals displayed.

SOURCE: Authors' own calculations using HRS linked SSA data.

Table 1: Summary Statistics by Uber Adoption Status

	Uber Before 2015 (1)	Uber After 2015 (2)	No Uber by 2019 (3)	Within State Difference (2)-(1) (4)
Total Population (1,000s)	288.77	113.33	60.31	-145.39***
Share Under 18	0.25	0.25	0.24	-0.01*
Share 18-30	0.16	0.17	0.16	0.01**
Share 30-54	0.35	0.33	0.33	-0.02***
Share 55-64	0.11	0.11	0.11	0.00
Share 65+	0.12	0.13	0.14	0.01***
Share White NH	0.77	0.79	0.81	0.01
Share Black NH	0.12	0.10	0.09	-0.02
Share Other NH	0.03	0.02	0.02	-0.01***
Share Hispanic	0.08	0.09	0.08	0.01
Share Male	0.49	0.49	0.50	-0.00
Share Female	0.51	0.51	0.50	0.00
Number of Establishments (1,000s)	8.18	2.81	1.57	-4.12***
Average Weekly Wages	676.09	602.60	582.75	-58.15***
Total Employment (1,000s)	130.67	48.79	24.16	-72.17***
Share Natural Resources	0.02	0.03	0.03	0.01
Share Construction	0.06	0.06	0.05	-0.00
Share Manufacturing	0.13	0.11	0.15	-0.01
Share Trade	0.19	0.20	0.19	-0.00
Share Information	0.01	0.01	0.01	-0.00
Share Finance	0.05	0.05	0.04	-0.00
Share Professional	0.09	0.07	0.06	-0.01*
Share Education/Health	0.11	0.12	0.12	0.01**
Share Hospitality	0.10	0.09	0.09	-0.01
Share Other	0.03	0.03	0.03	-0.00
Public Employment Share	0.18	0.20	0.20	0.01
Unemployment Rate	5.68	5.38	6.18	-0.15
Employment Rate	58.59	60.75	61.30	2.88
Median Home Value (1,000s)	116.15	81.79	82.62	-19.02***
SSDI Rate	3.90	4.23	5.04	0.32**
SSI Rate	1.95	2.24	2.67	0.27**
SNAP Rate	8.20	9.96	11.31	1.72***
Observations	6,228	1,557	8,360	

NOTE: Sample is restricted to counties between 2002 and 2020 that are in CBSAs. Outcomes are measured as cases per 100 residents. In column (4) only counties where Uber has entered by the end of the sample are included. In this specification state-by-year fixed effects are also included to make this a comparison between counties in the same state and year, some of which adopted Uber earlier, some of which adopted Uber later. Standard errors are corrected for clustering at the CBSA-level. Patterns are similar if I look at average changes between 2005 and 2011 or 2005 and 2019 by adoption status. p< 0.01 ***, p< 0.05 **, p<0.1 *.

Table 2: Effect of Access to Gig Opportunities Prevalence of Non-Employer Establishments

	Non-Employer Establishments per 100 Working-Age Adults							
	Total		Transportation		Passenger Transportation		Services	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Uber in CBSA	0.259***	0.251***	0.149***	0.139***	0.106***	0.087***	0.027***	0.020**
	(0.050)	(0.053)	(0.013)	(0.013)	(0.008)	(0.010)	(0.008)	(0.008)
Demeaned Unemployment Rate	0.058***	0.058***	0.017***	0.017***	0.011***	0.012***	0.004**	0.004**
	(0.012)	(0.012)	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)
Uber in CBSA*Unemployment Rate		-0.009		-0.011**		-0.021***		-0.008***
		(0.011)		(0.005)		(0.004)		(0.002)
Dependent Mean	10.87	10.87	0.60	0.60	0.10	0.10	1.17	1.17
Observations	34,110	34,110	34,088	34,088	32,445	32,445	34,096	34,096

NOTE: Sample is restricted to counties between 2002 and 2020 that are in CBSAs. Outcomes are measured as cases per 100 residents between 18 and 64. Many gig workers are classified as non-employer establishments, but this is a lower bound on the number of gig workers. Non-employer businesses are only included if total receipts exceed $1,000 in a year. Based on previous work (Farrell et al., 2018), many gig workers make much less than this in a year. Unemployment rates are measured at the annual, county level and de-meaned so that the direct effect of "Uber in CBSA" can be interpreted as the effect at the average level of unemployment. County and state-by-year fixed effects are included. Standard are clustered at the metropolitan area level. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *.

Table 3: Effect of Access to Gig Opportunities on County-level Social Program Caseloads

	SSDI Rate		SSI 18-64 Rate		SNAP Rate	
	(1)	(2)	(3)	(4)	(5)	(6)
Uber in CBSA	-0.167***	-0.119***	-0.067***	-0.043**	-0.677***	-0.496***
	(0.024)	(0.026)	(0.019)	(0.021)	(0.137)	(0.141)
Demeaned Unemployment Rate	0.003	-0.001	0.004	0.002	0.422***	0.411***
	(0.005)	(0.005)	(0.007)	(0.007)	(0.033)	(0.033)
Uber in CBSA*Unemployment Rate		0.052***		0.026***		0.211***
		(0.007)		(0.008)		(0.042)
Dependent Mean	5.16	5.16	2.57	2.57	12.48	12.48
Observations	30,518	30,518	34,105	34,105	27,847	27,847

NOTE: Sample is restricted to counties between 2002 and 2020 that are in CBSAs. Outcomes are measured as cases per 100 residents. SSI rates only count SSI cases for individuals between 18 and 64. Unemployment rates are measured at the annual, county level and de-meaned so that the direct effect of "Uber in CBSA" can be interpreted as the effect at the average level of unemployment. County and state-by-year fixed effects are included. Standard are clustered at the metropolitan area level. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *.

Table 4: Effect of Access to Gig Opportunities on Individual-level Program Participation from American Community Survey

	Any SSA (OASDI)*100		Any SSI*100		Any Welfare*100		Any SNAP*100		Any Public Insurance*100	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Uber in CBSA	-0.123***	-0.123**	-0.171***	-0.200***	-0.049	-0.053	-0.296	-0.519**	0.184	-0.522***
	(0.042)	(0.048)	(0.039)	(0.040)	(0.044)	(0.050)	(0.181)	(0.211)	(0.282)	(0.177)
Demeaned Unemployment Rate	0.016	0.016	0.020	0.017	0.052**	0.051**	0.647***	0.621***	-0.335*	-0.340**
	(0.014)	(0.015)	(0.014)	(0.014)	(0.024)	(0.024)	(0.093)	(0.090)	(0.175)	(0.140)
Uber in CBSA*Unemployment Rate		-0.000		0.028**		0.004		0.218***		0.581***
		(0.013)		(0.011)		(0.012)		(0.058)		(0.091)
Dependent Mean	2.82	2.82	2.27	2.27	1.53	1.53	10.74	10.74	14.37	14.37
Observations	18,125,445	18,125,445	18,125,445	18,125,445	18,125,445	18,125,445	18,125,445	18,125,445	14,595,493	14,595,493

NOTE: Sample is restricted to adults 18-60 in the 2005 to 2019 ACS. Data on public insurance is only available starting in 2008. Unemployment rates are measured at the annual, metropolitan area level. Individuals not living in metropolitan areas are assigned the state remained unemployment rate. Outcomes are binary indicators, multiplied by 100, to be directly comparable to the county level estimates in Table 3. Observations are weighted using ACS individual sampling weights. Metropolitan area and state-by-year fixed effects are included. Standard are clustered at the metropolitan area level. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *.

Table 5: Effect of Access to Gig Opportunities on Individual-level Program Income from American Community Survey

	SSA Income		SSI Income		Welfare Income	
	(1)	(2)	(3)	(4)	(5)	(6)
Uber in CBSA	-18.887***	-19.485***	-15.302***	-17.857***	-2.244	-1.393
	(5.351)	(5.931)	(3.503)	(3.697)	(2.007)	(2.105)
Demeaned Unemployment Rate	1.673	1.603	3.176**	2.878**	2.254**	2.354**
	(2.089)	(2.104)	(1.401)	(1.413)	(1.003)	(1.020)
Uber in CBSA*Unemployment Rate		0.585		2.502**		-0.833
		(1.547)		(1.143)		(0.621)
Dependent Mean	329.60	329.60	207.62	207.62	53.26	53.26
Observations	18,125,445	18,125,445	18,125,445	18,125,445	18,125,445	18,125,445

NOTE: Sample is restricted to adults 18-60 in the 2005 to 2019 ACS. Unemployment rates are measured at the annual, metropolitan area level. Individuals not living in metropolitan areas are assigned the state remained unemployment rate. Outcomes are continuous number of dollars of income, as self-reported in the ACS, indexed to 2020 dollars using the personal consumption expenditure index for inflation. Observations are weighted using ACS individual sampling weights. Metropolitan area and state-by-year fixed effects are included. Standard are clustered at the metropolitan area level. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *.

Table 6: Effect of Access to Gig Opportunities on Individual-level Social Security Program Participation in the Health and Retirement Study

	Any SSDI Claimed		Any SSDI Received		Any SSI Claimed		Any SSI Received	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Uber in County	-0.026**	-0.024**	-0.022***	-0.022***	-0.034***	-0.034***	-0.002	-0.001
	(0.012)	(0.012)	(0.008)	(0.008)	(0.010)	(0.001)	(0.005)	(0.005)
Demeaned Unemployment Rate	0.001	-0.0002	0.00004	-0.0001	0.004***	0.004**	-0.0003	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Uber in County*Unemployment Rate		0.008***		0.001		0.004*		0.003**
		(0.003)		(0.002)		(0.002)		(0.001)
Dependent Mean	0.242	0.242	0.109	0.109	0.192	0.192	0.040	0.040
Observations	185,489	185,489	185,489	185,489	185,489	185,489	185,489	185,489

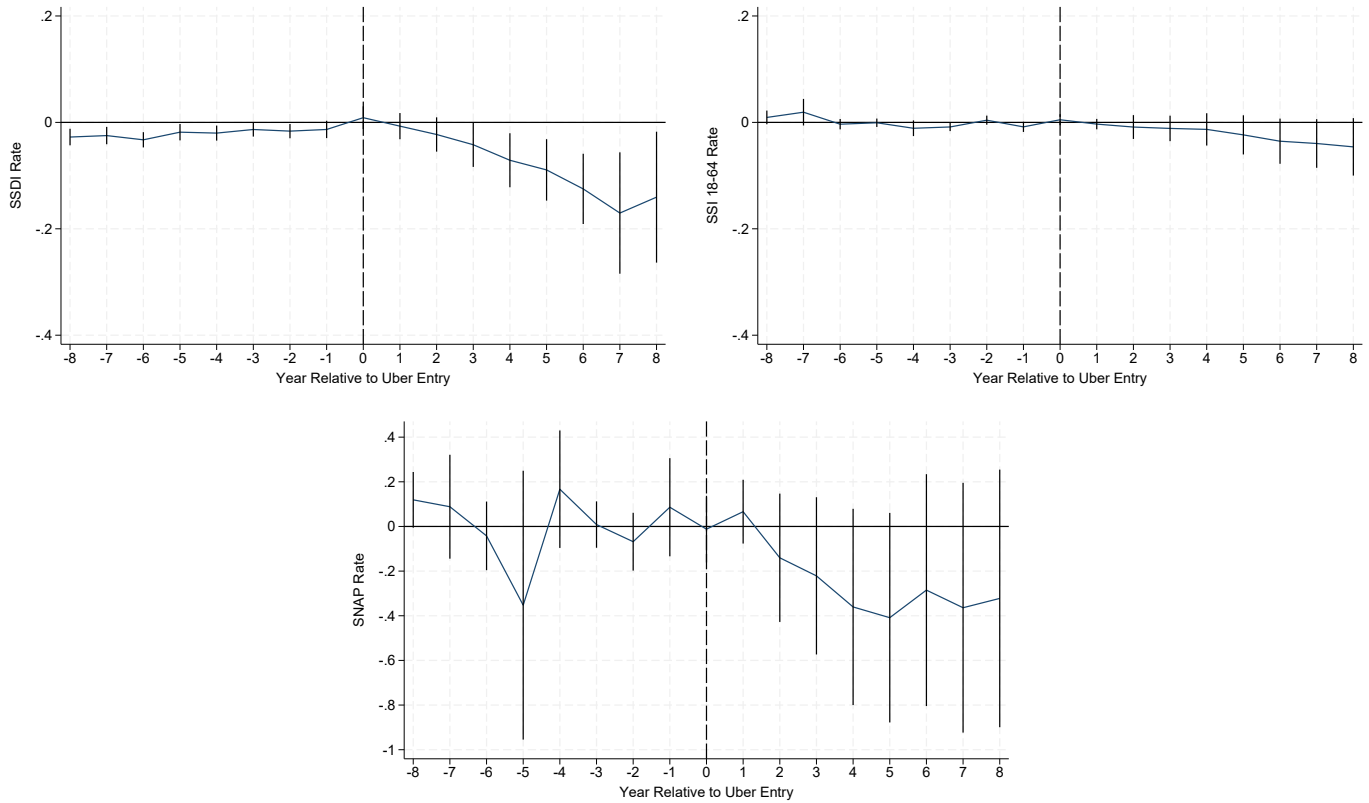
NOTE: Data come from matched SSA-HRS data from 1992 to 2020. Sample includes individuals aged younger than 70. Reported coefficients are from TWFE models as specified in equations (4) and (2). SSDI and SSI outcomes are derived from administrative SSA data. Observations are weighted using HRS individual sampling weights. All models include demographic control (age, marital status, gender, education, race/ethnicity, family size, immigrant status, veteran status, and self-reported health condition. County-state and year fixed effects are also included. Standard errors are clustered at county level. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *.

Table 7: Effect of Access to Gig Opportunities on Individual-level Labor Market Outcomes from American Community Survey

	Employed		Self Employed		Total Income		Wage Income		Family Income	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Uber in CBSA	0.006***	0.008***	0.001**	0.001*	-210.545	519.061***	-31.281	688.710***	-185.831	1368.084***
	(0.001)	(0.001)	(0.000)	(0.000)	(269.235)	(156.791)	(260.216)	(153.797)	(554.606)	(338.307)
Demeaned Unemployment Rate	-0.007***	-0.006***	0.000	0.000	-313.089**	-227.944**	-361.981***	-277.958***	-652.122**	-470.780**
	(0.001)	(0.001)	(0.000)	(0.000)	(141.362)	(112.422)	(132.281)	(103.685)	(283.879)	(220.463)
Uber in CBSA*Unemployment Rate		-0.002***		0.000		-714.388***		-704.974***		-1521.503***
		(0.000)		(0.000)		(181.668)		(180.111)		(335.628)
Dependent Mean	0.73	0.73	0.07	0.07	46776.07	46776.07	41030.74	41030.74	100507.46	100507.46
Observations	18,125,445	18,125,445	18,125,445	18,125,445	18,125,445	18,125,445	18,125,445	18,125,445	18,125,445	18,125,445

NOTE: Sample is restricted to adults 18-60 in the 2005 to 2019 ACS. Unemployment rates are measured at the annual, metropolitan area level. Individuals not living in metropolitan areas are assigned the state remained unemployment rate. Observations are weighted using ACS individual sampling weights. Metropolitan area and state-by-year fixed effects are included. Standard are clustered at the metropolitan area level. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *.

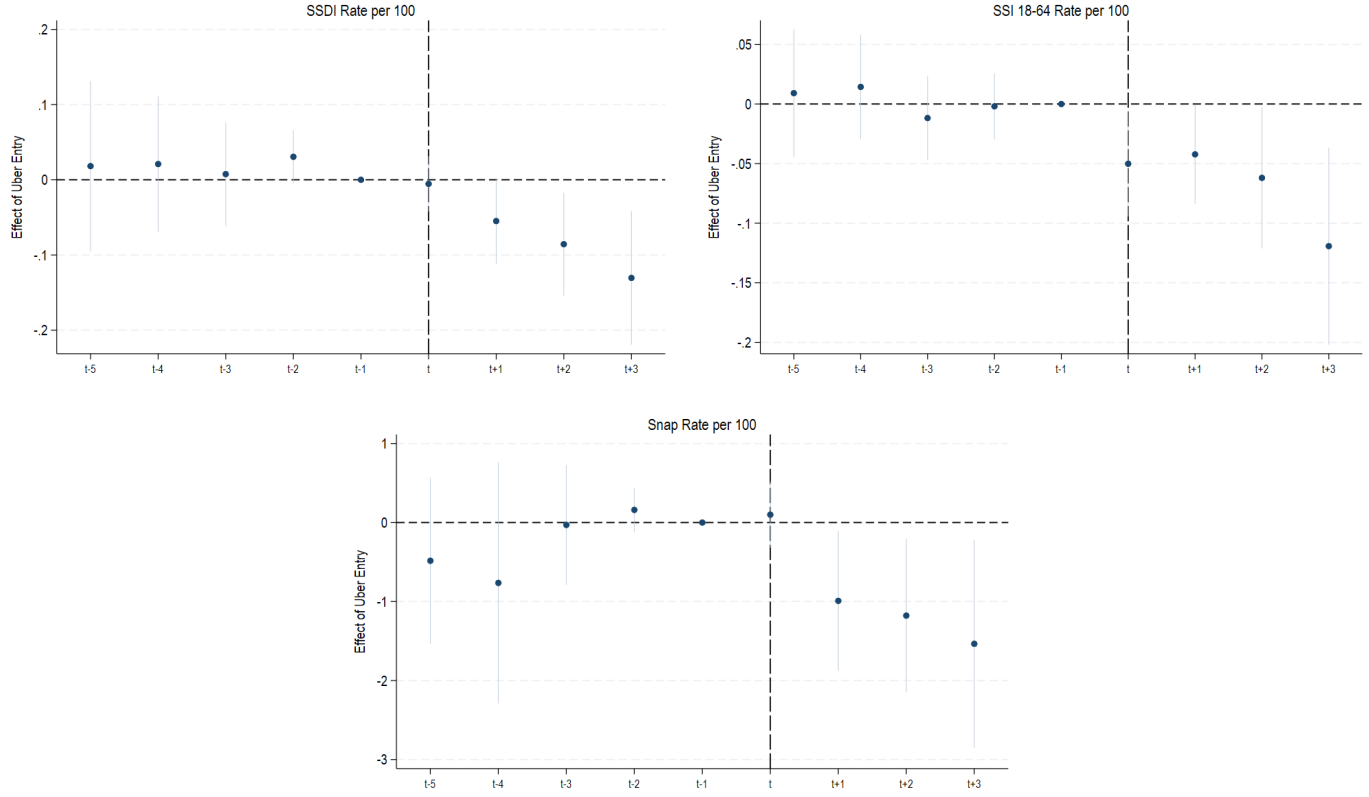
Figure A1: Doubly Robust Staggered-Timing Corrected Event Study Estimates of Uber Entry on County-level Program Caseloads: Not Yet Treated County Counterfactual



NOTE: Estimates obtained using doubly robust difference in difference event study methods, as proposed by Callaway and Sant'Anna (2020). Treated counties are compared to counties that are not yet treated. Only counties in CBSAs are included. Standard errors are clustered at the metropolitan area level, with 95-percent confidence intervals displayed.

SOURCE: Authors' own calculations using the county-level program caseload data.

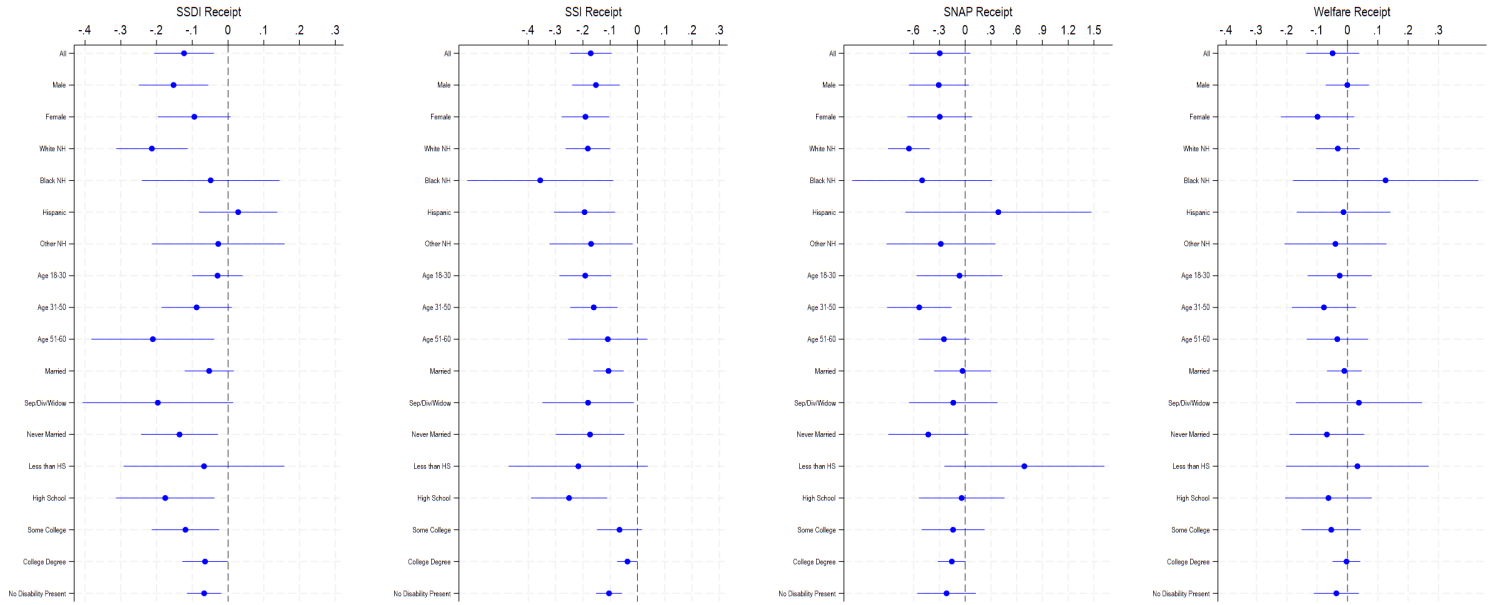
Figure A2: Stacked Event Study Effects of Uber Entry on Program Caseloads



NOTE: Estimates obtained from the stacked panel, where counties that gain access to Uber are compared to counterfactual counties that obtain access to Uber four years later. As such, a county-year observation might appear in the sample multiple times, once as a not-yet-treated counterfactual and once as a treated county similar to the method implemented by Deshpande and Li (2019). Only stacks for the 2010 through 2015 treatment year cohorts are included, so that each treatment cohort has a counterfactual cohort. Only counties in CBSAs are included. County fixed effects, stack by year fixed effects, and state by year fixed effects are included. Standard errors are clustered at the metropolitan area level, with 95-percent confidence intervals displayed.

SOURCE: Authors' own calculations using the county-level stacked panel.

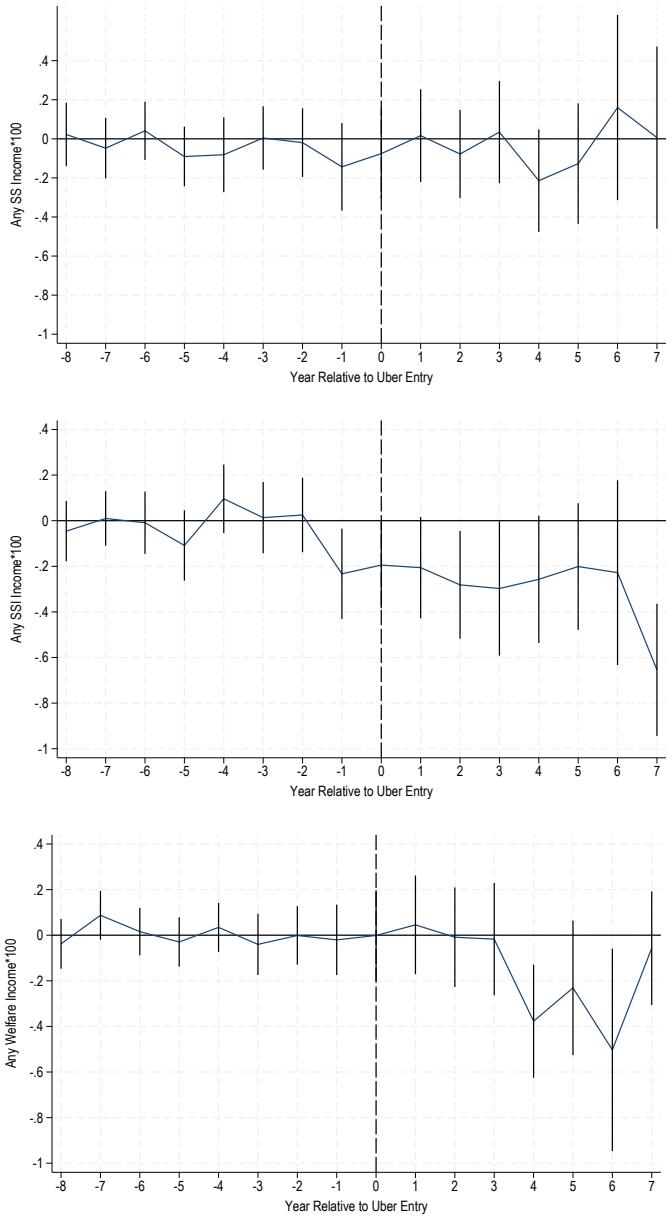
Figure A3: Heterogeneous Effects of Uber Entry on Program Participation



NOTE: Sample is restricted to adults 18-60 in the 2005 to 2019 ACS. Unemployment rates are measured at the annual, metropolitan area level. Individuals not living in metropolitan areas are assigned the state remained unemployment rate. Outcomes are continuous number of dollars of income, as self-reported in the ACS, indexed to 2020 dollars using the personal consumption expenditure index for inflation. Observations are weighted using ACS individual sampling weights. Metropolitan area and state-by-year fixed effects are included. Standard are clustered at the metropolitan area level, with 95-percent confidence intervals displayed.

SOURCE: Authors' own calculations using the county-level stacked panel.

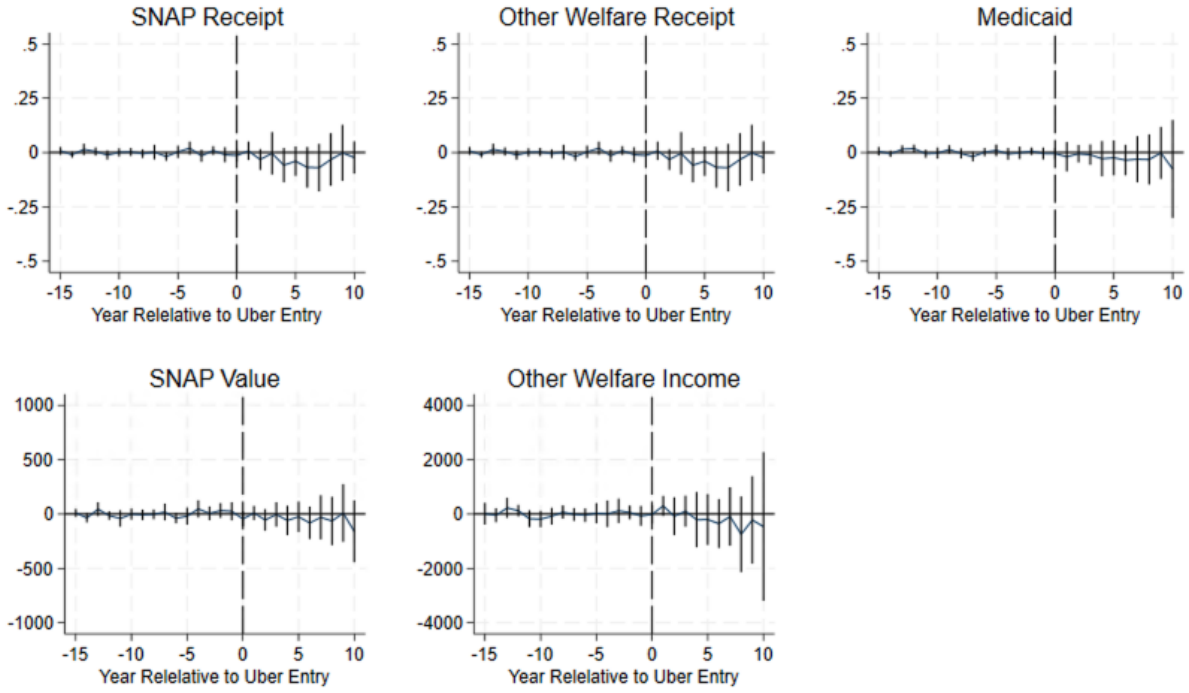
Figure A4: Staggered-Timing Corrected Event Study Effects of Uber Entry on Program Caseloads, ACS Aggregation



NOTE: Estimates obtained using doubly robust difference in difference event study methods, as proposed by Callaway and Sant'Anna (2020). Metropolitan area level by year estimates are produced from the ACS microdata for 18 to 60 year olds. Treated CBSAs are compared to CBSAs that are treated later. Standard errors are clustered at the metropolitan area level, with 95-percent confidence intervals displayed.

SOURCE: Authors' own calculations using the county-level stacked panel.

Figure A5: Staggered-Timing Corrected Event Study Effects of Uber Entry on Other Welfare Program, Health and Retirement Study Sample



NOTE: Estimates obtained using CSDiD models as specified in Eq.(3). Data come from matched SSA-HRS data from 1992 to 2020. Sample includes working individuals aged younger than 70. For each outcome, the coefficient and its 95 percent confidence intervals display the estimate - sigma - from Eq.(3). All models include demographic control (age, marital status, gender, education, race/ethnicity, family size, immigrant status, veteran status, and self-reported health condition. County-state and year fixed effects are also included. Standard errors are clustered at county level.

Table A1: Stacked Panel Effect of Access to Gig Opportunities on County-level Social Program Caseloads

	SSDI Rate		SSI 18-64 Rate		SNAP Rate	
	(1)	(2)	(3)	(4)	(5)	(6)
Treated*Post	-0.086**	-0.088*	-0.069**	-0.071**	-0.632	-0.654*
	(0.040)	(0.047)	(0.032)	(0.031)	(0.399)	(0.375)
Demeaned Unemployment Rate	0.005	-0.001	0.003	0.000	0.499***	0.479***
	(0.010)	(0.009)	(0.007)	(0.007)	(0.068)	(0.064)
Treated*Post*Unemployment Rate		0.056***		0.029**		0.264***
		(0.010)		(0.013)		(0.057)
Dependent Mean	4.76	4.76	2.25	2.25	12.69	12.69
Observations	12,552	12,552	12,552	12,552	10,854	10,854

NOTE: Estimates obtained from the stacked panel, where counties that gain access to Uber are compared to counterfactual counties that obtain access to Uber four years later. As such, a county-year observation might appear in the sample multiple times, once as a not-yet-treated counterfactual and once as a treated county. Only stacks for the 2010 through 2015 treatment year cohorts are included, so that each treatment cohort has a counterfactual cohort. Outcomes are measured as cases per 100 residents. Unemployment rates are measured at the annual, county level. Only counties in CBSAs are included. County fixed effects, stack by year fixed effects, and state by year fixed effects are included. Standard are clustered at the metropolitan area level. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *.

Table A2: Robustness: Effect of Access to Gig Opportunities on County-level Caseloads

	Baseline	Population Weighted	State and Year F.E.	Adopt by 2014	Exclude 2010 Adopters	Population Control	Demographic Controls
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Outcome: SSDI Rate			
Uber in CBSA	-0.167***	-0.269***	-0.165***	-0.061***	-0.166***	-0.121***	-0.132***
	(0.024)	(0.023)	(0.033)	(0.020)	(0.025)	(0.025)	(0.021)
Dependent Mean	5.16	5.16	5.16	4.46	5.17	5.16	5.15
Observations	30,518	30,518	30,527	11,767	30,399	30,518	29,689
				Outcome: SSI 18-64 Rate			
Uber in CBSA	-0.067***	-0.104***	-0.052**	-0.035***	-0.067***	-0.050**	-0.058***
	(0.019)	(0.021)	(0.024)	(0.013)	(0.019)	(0.019)	(0.018)
Dependent Mean	2.57	2.57	2.57	2.07	2.57	2.57	2.56
Observations	34,105	34,105	34,124	13,149	33,972	34,105	33,149
				Outcome: SNAP Rate			
Uber in CBSA	-0.677***	-0.410***	-0.514**	-0.407***	-0.661***	-0.669***	-0.713***
	(0.137)	(0.126)	(0.199)	(0.150)	(0.138)	(0.137)	(0.126)
Dependent Mean	12.48	12.48	12.49	10.67	12.52	12.48	12.39
Observations	27,847	27,847	27,866	11,361	27,714	27,847	27,121

NOTE: Sample is restricted to counties between 2002 and 2020 that are in CBSAs. Outcomes are measured as cases per 100 residents. SSI rates only count SSI cases for individuals between 18 and 64. All models control for the unemployment rate. Unless specified otherwise, county and state-by-year fixed effects are included. Column (2) weights counties by the total county population in 2002 at the beginning of the sample period. Column (3) includes state and year fixed effects separately. Column (4) only includes counties where Uber was adopted in 2014 or earlier. Column (5) excludes counties that adopted Uber in 2010, the first year. Column (6) controls for county-level population, race shares, gender shares, and age bin shares (under 18, 18-30, 30-54, 55-64, over 64), county-level industry shares, and the county-level median house price. Standard are clustered at the metropolitan area level. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *.

Table A3: Effect of Access to Gig Opportunities on Individual-level Other Welfare Program Participation in the Health and Retirement Study

	Any Food Stamps Received		Any Welfare Received		Any Medicaid Enrolled	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Sample from matched HRS-SSA						
Uber in County	-0.013*	-0.013	-0.020*	-0.019*	-0.010	-0.010
	(0.008)	(0.008)	(0.010)	(0.010)	(0.007)	(0.007)
Demeaned Unemployment Rate	0.003***	0.002*	0.004***	0.002*	0.001	0.00004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Uber in County*Unemployment Rate		0.006***		0.008***		0.007***
		(0.002)		(0.002)		(0.002)
Dependent Mean	0.072	0.072	0.113	0.113	0.074	0.074
Observations	90.205	90.205	90.205	90.205	90.205	90.205
Panel B: Sample from HRS data						
	Any Food Stamps Received		Any Welfare Received		Any Medicaid Enrolled	
	(1)	(2)	(3)	(4)	(5)	(6)
Uber in County	-0.017***	-0.017**	-0.021***	-0.021***	-0.013**	-0.013**
	(0.007)	(0.007)	(0.008)	(0.08)	(0.005)	(0.005)
Demeaned Unemployment Rate	0.003***	0.002***	0.004***	0.003***	0.002*	0.0002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Uber in County*Unemployment Rate		0.006***		0.006***		0.007***
		(0.002)		(0.002)		(0.002)
Dependent Mean	0.066	0.066	0.102	0.102	0.070	0.070
Observations	154,419	154,419	154,419	154,419	154,419	154,419

NOTE: For Panel A, data come from matched SSA-HRS data from 1992 to 2020. For Panel B, data come from HRS data from 1992-2020. Sample includes individuals aged younger than 70. Coefficients reported are from TWFE models as specified in Eq.(3) and Eq.(4). Other welfare outcomes: food stamp, welfare,and Medicaid are self-reported in HRS data. Observations are weighted using HRS individual sampling weights. All models include demographic control (age, marital status, gender, education, race/ethnicity, family size, immigrant status, veteran status, and self-reported health condition. County-state and year fixed effects are also included. Standard errors are clustered at county level. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *

Table A4: Effect of Access to Gig Opportunities on Individual-level Weffare Income in the Health and Retirement Study

	SSDI Income		SSI Income		Food Stamps Dollars		Welfare Income	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Sample from matched HRS-SSA								
Uber in County	-201.060	-201.530	-2.351	0.581	-16.245	-16.143	-89.031	-88.950
	(139.360)	(137.540)	(37.580)	(37.751)	(14.318)	(14.342)	(106.050)	(105.980)
Demeaned Unemployment Rate	16.005	16.319	1.768	-0.161	6.794***	6.216***	20.265	19.808
	(17.531)	(17.941)	(6.031)	(5.646)	(2.020)	(2.113)	(16.168)	(16.809)
Uber in County*Unemployment Rate		-2.784		17.065*		3.541		2.797
		(33.710)		(9.874)		(4.165)		(26.808)
Dependent Mean	1,499.05	1,499.05	225.28	225.28	125.86	125.86	743.29	743.29
Observations	185,489	185,489	185,489	185,489	90,205	90,205	90,205	90,205
Panel B: Sample from HRS data								
	SSDI Income		SSI Income		Food Stamps Dollars		Welfare Income	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Uber in County	-91.072	-90.612	-16.860	-16.821	-26.052**	-25.878**	71.595	-71.689
	(64.309)	(64.331)	(22.716)	(22.730)	(10.638)	(10.647)	(56.687)	(59.610)
Demeaned Unemployment Rate	2.395	-0.405	6.827*	6.592*	6.073***	5.017***	16.348	16.919
	(9.065)	(9.809)	(3.577)	(3.850)	(1.489)	(1.574)	(11.584)	(12.360)
Uber in County*Unemployment Rate		14.265		1.196		5.382*		-2.911
		(15.141)		(6.625)		(3.110)		(15.356)
Dependent Mean	730.652	730.652	207.571	207.571	111.446	111.446	603.659	603.659
Observations	154,419	154,419	154,419	154,419	154,419	154,419	154,419	154,419

NOTE: For Panel A, data come from matched SSA-HRS data from 1992 to 2020. For Panel B, data come from the HRS data from 1992 to 2020. The sample includes individuals aged less than 70 years. Coeficients reported are from TWFE models as specified in Eq.(3) and Eq.(4). SSDI and SSI outcomes are derived from annual SSA data while food stamp, welfare,and Medicaid outcomes are self-reported in biannual HRS data. Observations are weighted using HRS individual sampling weights. All models include demographic control (age, marital status, gender, education, race/ethnicity, family size, immigrant status, veteran status, and self-reported health condition. County-state and year fixed effects are also included. Standard errors are clustered at county level. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *

Table A5: Effect of Access to Gig Opportunities on Individual-level Social Security Program Participation from Health and Retirement Study Data, CSDiD Models

	Any SSDI Claimed (1)	Any SSDI Received (2)	Any SSI Claimed (3)	Any SSI Received (4)	Any Food Stamps Received (5)	Any Welfare Received (6)	Any Medicaid Enrolled (7)
Uber in County	-0.066***	-0.033*	-0.034	0.007	-0.035**	-0.030	-0.018
	(0.023)	(0.019)	(0.021)	(0.011)	(0.018)	(0.022)	(0.014)
Demographics Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-level Unemployment Rate	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dependent Mean	0.242	0.109	0.192	0.040	0.072	0.113	0.074
Observations	185,489	185,489	185,489	185,489	90,205	90,205	90,205

NOTE: Data come from matched SSA-HRS data from 1992 to 2020. Sample includes individuals aged younger than 70. Reported Coeficients are from staggered difference in difference method, as proposed by Callaway and Sant'Anna (2020). SSDI and SSI outcomes are derived from SSA data while food stamp, welfare,and Medicaid outcomes are self-reported in HRS data. All models include demographic control (age, marital status, gender, education, race/ethnicity, family size, immigrant status, veteran status, and self-reported health condition. County-state and year fixed effects are also included. Standard errors are clustered at county level. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *.

Table A6: Effect of Access to Gig Opportunities on Individual-level Social Security Program Participation from Health and Retirement Study Data, CSDiD Models

	SSDI Income (1)	SSI Income (2)	Food Stamps Dollars (3)	Welfare Income (4)
Uber in County	-575.974*	12.973	-43.995	-130.661
	(308.611)	(74.209)	(30.606)	(203.607)
Demographics Control	Yes	Yes	Yes	Yes
County-level Unemployment Rate	Yes	Yes	Yes	Yes
Dependent Mean	1,500.68	225.23	125.86	743.29
Observations	185,489	185,489	90,205	90,205

NOTE: Data come from matched SSA-HRS data from 1992 to 2020. Sample includes individuals aged younger than 70. Reported Coeficients are from staggered difference in difference method, as proposed by Callaway and Sant'Anna (2020). SSDI and SSI outcomes are derived from SSA data while food stamp, welfare,and Medicaid outcomes are self-reported in HRS data. All models include demographic control (age, marital status, gender, education, race/ethnicity, family size, immigrant status, veteran status, and self-reported health condition. County-state and year fixed effects are also included. All monetary values are deflated in 2019 dollars. Standard errors are clustered at county level. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *.

Table A7: Effect of Access to Gig Opportunities on Individual-level Social Security Program Participation - No Sample Weights

	Any SSDI Claimed		Any SSDI Received		Any SSI Claimed		Any SSI Received	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Uber in County	-0.012	-0.014	-0.011*	-0.011*	-0.017*	-0.017*	0.011*	0.010*
	(0.012)	(0.012)	(0.006)	(0.006)	(0.010)	(0.010)	(0.006)	(0.090)
Demeaned Unemployment Rate	-0.001	-0.002	0.0002	0.0003	0.005***	0.005***	-0.0002	-0.0005
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Uber in County*Unemployment Rate		0.008***		-0.001		0.002		0.004***
		(0.003)		(0.001)		(0.003)		(0.001)
Dependent Mean	0.254	0.242	0.104	0.104	0.222	0.222	0.051	0.051
Observations	202,658	202,658	202,658	202,658	202,658	202,658	202,658	202,658

NOTE: Data come from matched SSA-HRS data from 1992 to 2020. Sample includes individuals aged younger than 70. Reported Coefficients are from TWFE models as specified in Eq.(4). SSDI and SSI outcomes are derived from SSA data while food stamp, welfare,and Medicaid outcomes are self-reported in HRS data. All models include demographic control (age, marital status, gender, education, race/ethnicity, family size, immigrant status, veteran status, and self-reported health condition. County-state and year fixed effects are also included. Standard errors are clustered at county level. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *.

Table A8: Effect of Access to Gig Opportunities on Individual-level Welfare Program Participation - No Sample Weights

	Any Food Stamps Received		Any Welfare Received		Any Medicaid Enrolled	
	(1)	(2)	(3)	(4)	(5)	(6)
Uber in County	0.007	0.006	0.005	0.003	0.014*	0.011
	(0.009)	(0.009)	(0.010)	(0.010)	(0.007)	(0.007)
Demeaned Unemployment Rate	0.003***	0.003***	0.004***	0.004***	0.001	-0.0001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Uber in County*Unemployment Rate		0.005**		0.007**		0.009***
		(0.002)		(0.003)		(0.002)
Dependent Mean	0.087	0.087	0.123	0.123	0.090	0.090
Observations	98,738	98,738	98,738	98,738	98,738	98,738

NOTE: Data come from matched SSA-HRS data from 1992 to 2020. Sample includes individuals aged younger than 70. Reported Coeficients are from TWFE models as specified in Eq.(4). SSDI and SSI outcomes are derived from SSA data while food stamp, welfare,and Medicaid outcomes are self-reported in HRS data. All models include demographic control (age, marital status, gender, education, race/ethnicity, family size, immigrant status, veteran status, and self-reported health condition. County-state and year fixed effects are also included. Standard errors are clustered at county level. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *

Table A9: Effect of Access to Gig Opportunities on Individual-level Program Income - No Sample Weights

	SSDI Income		SSI Income		Food Stamps Dollars		Welfare Income	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Uber in CSBA	-149.390	-143.220	76.168*	68.303	17.127	16.394	-22.912	-22.540
	(91.167)	(93.229)	(43.303)	(42.607)	(16.514)	(16.416)	(77.526)	(78.344)
Demeaned Unemployment Rate	10.492	12.349	-1.639	-4.006	9.686***	9.463***	14.849	14.962
	(12.264)	(12.242)	(6.500)	(5.988)	(2.942)	(3.061)	(10.290)	(10.290)
Uber in CSBA*Unemployment Rate		-28.715		36.597***		2.395		-1.217
		(21.523)		(10.882)		(4.511)		(19.383)
Dependent Mean	1,330.16	1,330.16	291.98	291.98	157.72	157.72	690.55	690.55
Observations	202,658	202,658	202,658	202,658	98,738	98,738	98,738	98,738

NOTE: Data come from matched SSA-HRS data from 1992 to 2020. Sample includes individuals aged younger than 70. Reported coefficients are from TWFE models as specified in Eq.(4). SSDI and SSI income outcomes are derived from SSA data while food stamp dollars and welfare income outcomes are self-reported in HRS data. All monetary values are indexed to 2019 dollars using the personal consumption expenditure index for inflation. All models include demographic control (age, marital status, gender, education, race/ethnicity, family size, immigrant status, veteran status, and self-reported health condition. County-state and year fixed effects are also included. Standard errors are clustered at county level. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *.

Table A10: Effect of Access to Gig Opportunities on Employment and Incomes in Health and Retirement Study

	Labor Force Participation		Self-Employment		Earnings		Household Income	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Uber in County	0.021*	0.021*	0.007	0.007	1,852.90**	1,847.90**	8,325.70***	8,325.30***
	(0.011)	(0.011)	(0.007)	(0.007)	(815.76)	(813.89)	(1,713.40)	(1,712.20)
Demeaned Unemployment Rate	-0.003*	-0.004*	0.002	0.002	-529.03***	-500.37***	-1,384.20***	-1,381.90***
	(0.002)	(0.002)	(0.001)	(0.001)	(133.26)	(134.35)	(294.22)	(289.08)
Uber in County*Unemployment Rate		0.001		0.002		-175.53		-14.24
		(0.003)		(0.002)		(191.41)		(423.43)
Dependent Mean	0.589	0.589	0.113	0.113	26,294.180	26,294.180	86,849.680	86,849.680
Observations	90,205	90,205	90,205	90,205	90,205	90,205	90,205	90,205

NOTE: Data come from matched HRS-SSA data from 1992 to 2020. Sample includes individuals aged younger than 70. Reported coeficients are from TWFE models as specified in Eq.(4). All outcomes are self-reported in HRS data. Values for Earnings and Household Income are winsorized at 5 percentiles of the distribution to minimize influence of extreme values. All monetary values are indexed to 2019 dollars using the personal consumption expenditure index for inflation. Observations are weighted using HRS individual sampling weights. All models include demographic control (age, marital status, gender, education, race/ethnicity, family size, immigrant status, veteran status, and self-reported health condition. County-state and year fixed effects are also included. Standard errors are clustered at county level. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *.

Table A11: Effect of Access to Gig Opportunities on Individual-level Social Security Program Participation - Self-reported

	Any SSDI Claimed		Any SSDI Received		Any SSI Claimed		Any SSI Received	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Uber in County	-0.003	-0.003	-0.006	-0.006	0.0004	0.0003	-0.002	-0.002
	(0.003)	(0.003)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)
Demeaned Unemployment Rate	0.001	0.001	-0.0003	-0.001	0.002***	0.002***	0.001*	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.0004)	(0.001)
Uber in County*Unemployment Rate		-0.001		0.002*		-0.001**		0.001
		(0.001)		(0.001)		(0.001)		(0.001)
Dependent Mean	0.035	0.035	0.077	0.077	0.023	0.023	0.038	0.038
Observations	154,419	154,419	154,419	154,419	154,419	154,419	154,419	154,419

NOTE: Data come from HRS data from 1992 to 2020. Sample includes working individuals aged younger than 70. Repored coeficients reported are from TWFE models as specified in Eq.(4). All outcomes are self-reported in HRS data. Observations are weighted using HRS individual sampling weights. All models include demographic control (age, marital status, gender, education, race/ethnicity, family size, immigrant status, veteran status, and self-reported health condition. County-state and year fixed effects are also included. Standard errors are clustered at county level. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *.