Alternative Insurance: Gig Work and Social Insurance Participation*

Ngoc Dao† Riley Wilson‡

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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 assistance 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

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†Kean University, Email: ndao@kean.edu.

‡Brigham Young University, IZA, CESifo, Email: riley_wilson@byu.edu.

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, 2021; 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), unemployment insurance, 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 social program receipt and program-level 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. We see some evidence of reductions in unemployment insurance and public insurance, although these outcomes have more limited availability. 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, 2021). 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 more than a 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 insurance 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, which carry bureaucratic burden and stigma, 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., 2018; Cook et al., 2020; Hall et al., 2023). 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. Using a difference-in-difference strategy exploiting the roll-out of gig work platforms and individuals' propensity to engage in gig work, Jackson (2022) finds a consistent pattern. Recently unemployed, older workers are about 6 percentage points less likely to participate in disability insurance when gig work is available. 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 and safety net programs 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 if they view it as an alternative way to insure.

For example, if a worker loses their job, becomes disabled, or faces some other idiosyn-

cratic shock that reduces their income they can choose to participate in social programs which offer a benefit, but also impose costs, such as stigma, administrative burdens (Deshpande and Li, 2019), 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 and other safety net programs. First, when individuals experience negative income shocks that trigger program eligibility, they may instead choose to smooth income shocks through flexible, on-demand employment, since applying and maintaining eligibility for these programs is costly. 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 extent 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., 2025), 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., 2025) 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, AirBnB, 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 (CBSAs), which we refer to as metropolitan areas. 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

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

that year. The second is a county-level 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). It would be particularly concerning if Uber entered better performing labor markets earlier, as this could directly affect social program participation. As seen in Table 1, although the counties that Uber entered earlier are more populous and have a larger labor market, they are quite similar along many other demographic and labor market dimensions. If anything, the places Uber entered first have slightly higher unemployment rates. As discussed later, we conduct specification sensitivity analysis and examine pre-trends to verify that differences in program participation are not due to differential selection along these dimensions in the places Uber entered earlier.

[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.

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 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. Although adjustments to unemployment insurance would provide a natural outcome of interest, unemployment insurance caseloads are not available at the county-level. However, using IRS statistics of income data we can also capture measures of the number of returns with unemployment insurance income and the number of returns with a Schedule C (to proxy for households with self-employment).[6] 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

[6]These measures ar produced at the zip code level which we convert to county level estimates using zip code to county population crosswalks.

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.[7]

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 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. We supplement this with IRS measures of the number of tax returns with Schedule C self-employment earnings. 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. Even though the majority of platform work comes from the transportation sector (Farrell et al., 2018; Garin et al., 2023), the number of transportation non-employers from the national Nonemployer Statistics only captures 40 percent of the rise in gig workers documented by Jackson (2022). For this reason, we do not interpret these measures as the "first stage" effect of gig work access on gig employment, but rather as sug-

[7]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.

gestive 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 (labeled "welfare income" in the ACS) 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.[8] 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

[8]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.

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 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.[9] The matched HRS-SSA data resulted in roughly 185,000 observations between 1992 and 2020 in the analytic sample.[10] Importantly, we note that the HRS captures an older population with much higher rates of program eligibility and participation that is captured in the county caseload and ACS data. Differences in point estimates should be interpreted

[9]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.

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

in this light.

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. Across all specifications, the analysis uses weighted HRS data to generalize our findings to the general population [11]. 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 effects of gig opportunity access on social program participation. Our empirical approach proceeds in three steps. We first establish that Uber entry increased gig employment in treated areas, then estimate the effects of Uber availability on program participation using county- and individual-level specifications, and finally assess robustness to the choice of estimator under staggered treatment timing.

Before estimating downstream effects on program participation, we verify that Uber entry generated meaningful increases in gig work activity in treated areas. This first-order check is essential: if Uber entry did not expand gig employment, any downstream effects on program participation cannot credibly be attributed to the gig employment channel. We document the effects of Uber availability on the number of non-employer establishments per 100 working-age adults (18–64) and the self-employment rate as direct measures of gig

[11] Unweighted estimates were also computed as a robustness check; while results are directionally consistent, magnitudes differ in some specifications. Results are presented upon request

employment prevalence. We then use this evidence to motivate the program participation analysis that follows.

We leverage the differential timing of Uber's deployment across cities as a plausibly exogenous source of variation in gig employment opportunities. As noted above, Uber generally rolled out first to the largest cities by population, but not for reasons directly related to social program participation. Because local population is relatively stable over our sample period, our difference-in-differences estimates absorb differences in population levels and other fixed local characteristics that might otherwise confound the relationship between Uber entry timing and outcomes. We therefore restrict the analysis to counties and individuals in metropolitan areas, which are broadly comparable in population.

While Uber's decision to enter a particular metropolitan area may not be fully exogenous, the timing of its expansion – conditional on eventual entry– is more plausibly unrelated to local characteristics that drive program participation. To support this assumption, we focus comparisons on early- versus late-adopting counties within the same state, which are substantially more similar to one another than either group is to counties where Uber never entered. As shown in columns (1) and (2) of Table 1, early- and late-adopting counties differ significantly along only a few dimensions, lending credibility to the identifying assumption. We further estimate event study specifications to verify that treated counties do not exhibit differential pre-treatment trends relative to later-adopting counties. 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.

County-Level Specifications

For county-level outcomes, we estimate the following baseline two-way fixed effects regression:

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

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) and IRS returns with Schedule C rates to capture the rate of self-employment and to determine if gig work access affects the prevalence 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.

One concern is that Uber may disproportionately expand into areas with improving labor markets, which would independently affect program participation. If anything, the evidence points in the opposite direction — Uber first expanded to counties with slightly higher unemployment rates (Table 1).[12] Nevertheless, to verify that our estimates are not confounded by differential labor market trends, we provide event study estimates to assess pre-trends and report specifications that directly control for the annual county-level de-meaned unemployment rate in Appendix Table A1. Our results are stable across these specifications. We cluster standard errors at the metropolitan area level throughout, consistent with the level at which Uber launched and treatment was assigned. For most outcomes we estimate reduced-form effects, as there is no consensus on how to reliably identify gig workers in government surveys or administrative caseload data (United States Government Accountability Office, 2017) and the Non-employer Statistics likely undercount many gig workers. The individual-level data nonetheless allow us to explore heterogeneous effects and assess which groups'

[12]Consistent with this, replacing the outcome in equation (1) with the annual county unemployment rate yields a marginally significant ($p = 0.064$) estimated increase of 0.09 percentage points associated with Uber operating in the county.

program participation is most sensitive to expanded gig employment opportunities.

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).

Beyond the average effect, we are also interested in whether gig work and social program participation serve as substitute forms of insurance against economic shocks. To examine this, we augment equation (1) with the direct effect of local unemployment and its interaction with Uber availability:

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

The δ coefficient provides an estimate of how Uber access changes program participation as the unemployment rate rises.[13] This will allow us to determine if the substitution away from

[13]As seen in Appendix Tables A1 and A1, the direct effect of Uber access is not changed by controlling for unemployment rates.

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. This specification also allows us to verify that the estimated effects of Uber entry are not being biased by local economic conditions and not sensitive to controlling for the unemployment rate (Table A1).

Individual-Level Specifications

We estimate analogous specifications at the individual level using the ACS and HRS:

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

and

$$Participate_{ict} = \theta_m + \lambda_{st} + \beta UberOperating_{mst} + \gamma Urate_{mt} + \delta UberOperating_{mst} \times Urate_{mt} + \varepsilon_{ist} \tag{4}$$

In the ACS, treatment and unemployment are assigned at the metropolitan area (CBSA) level because county identifiers are not available for all respondents. In the HRS, county-level identifiers are available, allowing us to assign treatment at the county level. The ACS and HRS allow us to explore individual-level heterogeneity and determine which groups' program participation are most sensitive to gig opportunities.

Robustness to Staggered Treatment Timing

A well-established concern in the recent econometrics literature is that two-way fixed effects regressions with staggered treatment timing can produce misleading estimates when treatment effects are heterogeneous across cohorts, due to implicit negative weighting of some treated units (Callaway and Sant'Anna, 2020; de Chaisemartin and D'Haultfœuille, 2020;

Goodman-Bacon, 2021). We address this concern using two complementary approaches that are robust to staggered adoption. The first is a stacked panel design following Deshpande and Li (2019) and Gentry (2025). We assign each county to an Uber entry-year cohort and match it with all counties where Uber entered exactly four years later. We then stack the event study panels across cohorts to create a dataset where we can compare the effect of treatment relative to similar counties that receive treatment four years later and estimate the average effect of treatment relative to counties that were treated exactly four years later. This design maintains a consistent and clean comparison group for each treated unit over time, avoiding the contaminated comparisons between earlier and later adopters that can arise in standard TWFE estimation.

The second approach uses the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2020) — hereafter CSDiD — which constructs cohort-specific average treatment effects and aggregates them in a way that eliminates negative weighting. This is particularly relevant given that counties where Uber had not entered by 2019 differ substantially from expansion counties along several dimensions (Table 1), raising concerns about whether never-treated counties provide a credible counterfactual. The CSDiD estimator addresses this by using not-yet-treated counties as the comparison group. One limitation of the CSDiD framework is that it does not readily accommodate models with interacted continuous treatments, such as our Uber-by-unemployment-rate specifications. For this reason, we treat the CSDiD estimates as a robustness check reported in the appendix, while the TWFE and stacked panel models serve as our primary specifications. The consistency of results across all three approaches strengthens confidence that our findings are not driven by a particular methodological choice.

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 0.262. More than half of this increase is driven by the transportation sector, and passenger transportation specifically, consistent with the expansion of Uber services. But the gap suggests the roll-out of Uber also increases the number of non-employer businesses in other industries, consistent with Uber's entry proxying for broader access to gig opportunities. Estimates are similar when we include the interaction between Uber access 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., 2025) 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 those estimated in Table 2. Consistently, we find that when Uber begins operating, the number of tax returns with a Schedule C for self-employment income increases by 0.51 per 100 working-age adults.[14] 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 provide stacked-panel event-study estimates on the number of non-employer estab-

[14]This measure is also unlikely to capture all gig workers.

lishments in Figure A1. We observe flat pre-trends in the number of transportation and services establishments, followed by rapid post-entry growth. 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, consistent with the patterns observed in Jackson (2022). 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 0.64 SNAP recipients per 100 residents (5.4 percent).[15] These results suggest that when there is increased access to gig opportunities fewer people participate in social insurance and transfer programs. The SSDI and SSI estimates are about an eighth to half as large as our estimated effects on the number of non-employer establishments and self-employed, 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., 2025), 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.[16]

We next interact the presence of Uber with the local, demeaned unemployment rate.[17]

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

[16]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.

[17]The relationship between Uber availability and the outcomes does not change meaningfully when we include the unemployment rate (A1. Once concern is that unemployment rates are endogenous to current

At the average unemployment rate, access to gig opportunities reduces SSDI and SSI participation at approximately the same rate as in the previous specification (SNAP participation is reduced by less). 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 lessened 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.

Although unemployment insurance (UI) participation is another natural outcome of interest, it is not reported at the county-level. Using the IRS SOI, we are able to capture the number of returns with unemployment insurance income in 2002 and 2004 through 2020. We find that UI participation falls by 0.14 cases per 100 working-age adults when Uber enters the area, but this substitution is sensitive to local economic conditions. Only in strong labor markets (unemployment rate below the mean) do we see substitution away from UI (A2).[18]

5.3 Robustness

In Table A3 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 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

events. We find similar events if we use one-year lagged unemployment rates A1.

[18]There is more evidence of pre-trends for this unemployment insure measure (A2, so we interpret these results with caution.

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., 2023). 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.[19]

5.4 Staggered Treatment Timing Corrections

Our results are robust to stacked panel methods to account for staggered treatment timing (Deshpande and Li, 2019; Goodman-Bacon, 2021). In Table 4 we estimate that being exposed to Uber decreases SSDI enrollment rates by 0.088, SSI enrollment rates by 0.07, and SNAP participation rates by 0.89 relative to counties that Uber enters exactly four years later. We also observe that the degree of substitution away from SSDI, SSI, and SNAP falls as the unemployment rate rises.

We also provide event study evidence based on the stacked panel in Figure 3. 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 4 caseloads in SSDI and SNAP fall significantly and stay lower by about -0.1 cases (for SSDI and SSI) and -1 case (for SNAP) for the next three years after Uber's entry.

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, 2021). Event studies are provided in Figure A4. 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.[20] The declines in SSDI and SSI are statistically

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

[20]CSDiD calculates pre-period patterns by calculating year-to-year differences which might understate

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 A3 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.

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 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 stacked panel estimates to account for staggered treatment in the appendix (see Table A4 and Figure A5). 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 5. 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

the degree of pre-trend deviations. This is another reason we rely on the stacked panel analysis.

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 smaller, and less consistent than the county-level estimates. We find some evidence of reductions in public insurance use. We do not see the same pattern of substitution between Uber and SSDI participation falling as the unemployment rate rises, but we do when looking at SSI, SNAP, and public insurance use. Like the county-level caseload analysis, these data suggest 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 6 we look at the amount of income individuals have from the Social Security Administration, from Supplemental Security Income, and from welfare payments.[21] Access to gig opportunities, as proxied by availability of Uber, is associated with a $19.02 reduction in annual SSA income and a $15.56 reduction in annual SSI income. Once again, these represent intent to treat estimates. The effect on transfer income dollars is negative but insignificant.

The ACS individual-level data also allows us to document heterogeneous effects across different demographic groups (Figure A6). 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

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

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 7 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 7).[22] The larger effects observed in the HRS data, relative to those in the county-level data and the ACS data, is due to the fact that the HRS sample contains 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 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

[22]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.

may serve as a substitute for welfare participation in such settings.

Appendix Table A5 presents the results for the participation in other welfare programs, where we find similar patterns.[23] 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 A6).

As noted above, stacked event study and CSDiD 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. However, if use the ACS microdata, collapsed to the CBSA-by-year level, and estimate CSDiD event study effects we see noisy, but consistent patterns (Figure A8). 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 A7 and A9. 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 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.[24]

[23]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

[24]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.

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 8 and A12). 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 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.[25] 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 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

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

when labor market conditions are favorable.[26] 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 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. In-

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

creased 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.

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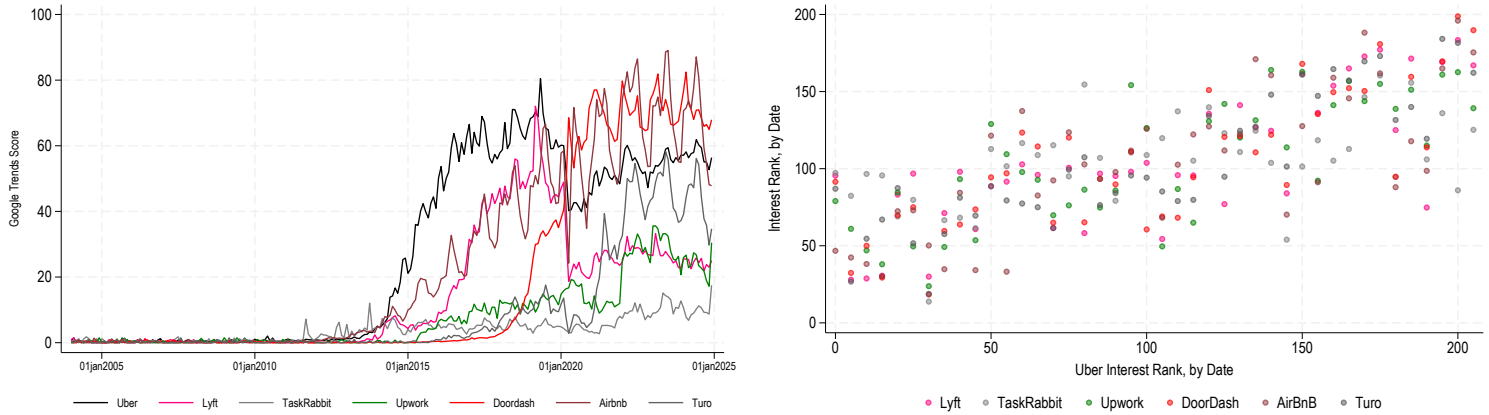
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Tables and Figures

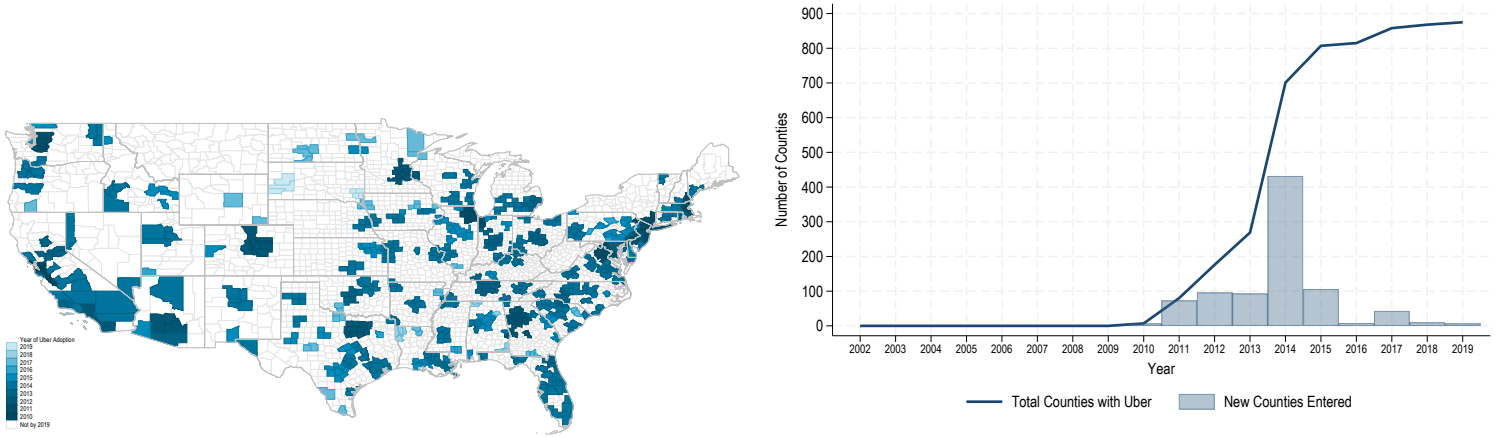
Figure 1: Roll-out of Uber Pre-dates and Predicts Other Gig Platform Roll-out Across Geography and Time



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.

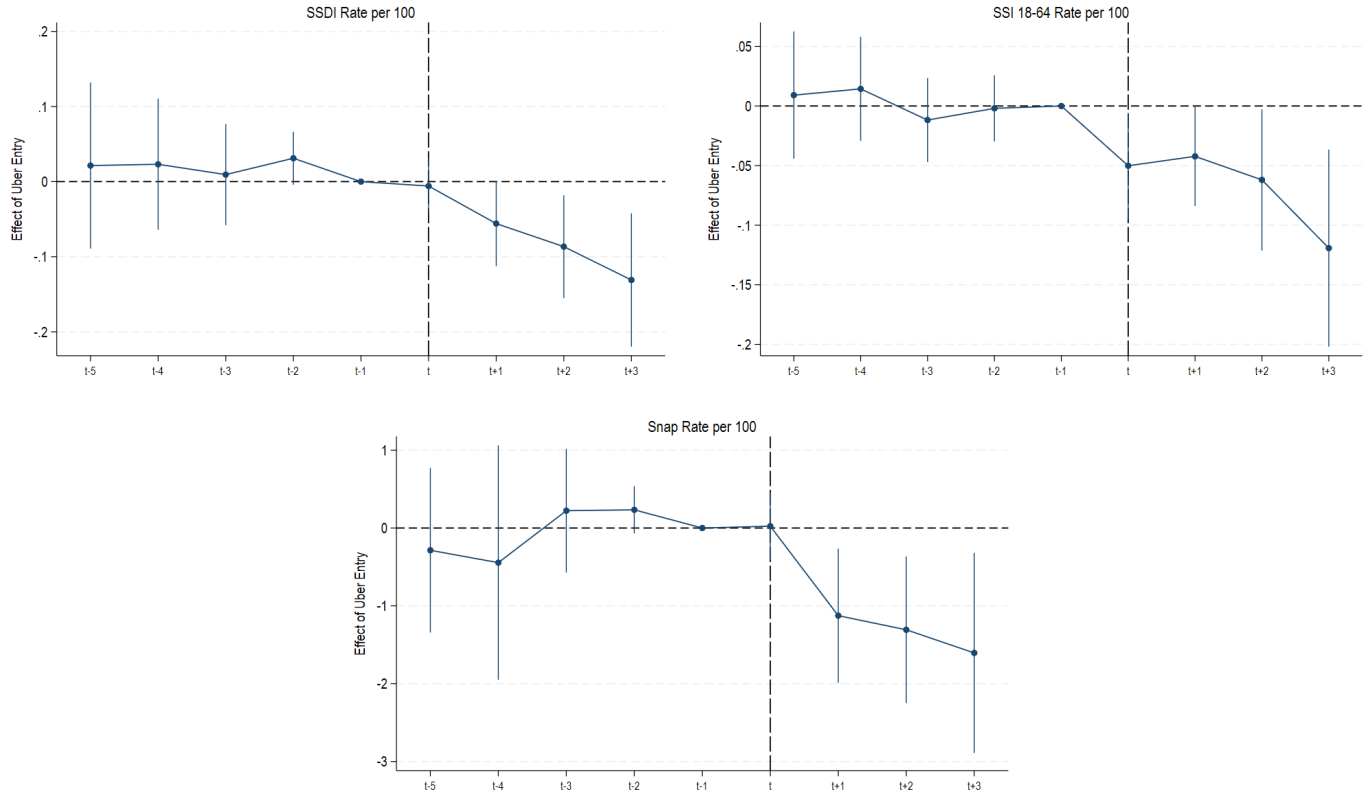
Figure 2: Roll-out of Uber Across Counties and Time



NOTE: On the left the year Uber began operating in the metropolitan area is provided. On the right 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: Stacked Event Study Effects of Uber Entry on County-level 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. Estimates are from a stacked panel specification with 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.

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 Self-Employment and Non-Employer Establishments

	Non-Employer Establishments per 100 Adults				Returns with Schedule C	
	Total		Transportation		per 100 Adults	
	(1)	(2)	(3)	(4)	(5)	(6)
Uber in CBSA	0.262***	0.251***	0.150***	0.139***	0.505***	0.510***
	(0.050)	(0.053)	(0.012)	(0.013)	(0.063)	(0.068)
Demeaned Unemployment Rate		0.058***		0.017***		0.014
		(0.012)		(0.004)		(0.013)
Uber in CBSA*Unemployment Rate		-0.009		-0.011**		0.006
		(0.017)		(0.011)		(0.005)
Dependent Mean	10.87	10.87	0.60	0.60	10.04	10.04
Observations	34,110	34,110	34,088	34,088	32,294	32,294

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. Estimates are from a two-way fixed effects specification with 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**	-0.643***	-0.496***
	(0.024)	(0.026)	(0.019)	(0.021)	(0.137)	(0.141)
Demeaned Unemployment Rate		-0.001		0.002		0.411***
		(0.005)		(0.007)		(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. Estimates are from a two-way fixed effects specification with 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: 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	-0.088**	-0.088*	-0.070**	-0.071**	-0.890**	-0.654*
	(0.040)	(0.047)	(0.031)	(0.031)	(0.418)	(0.375)
Demeaned Unemployment Rate		-0.001		0.000		0.479***
		(0.009)		(0.007)		(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	12,566	12,552	12,566	12,552	10,868	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. Estimates are from a stacked panel specification with 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 5: 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	-0.124***	-0.123**	-0.173***	-0.200***	-0.053	-0.053	-0.348*	-0.519**	0.186	-0.522***
	(0.042)	(0.048)	(0.039)	(0.040)	(0.044)	(0.050)	(0.183)	(0.211)	(0.299)	(0.177)
Demeaned Unemployment Rate		0.016		0.017		0.051**		0.621***		-0.340**
		(0.015)		(0.014)		(0.024)		(0.090)		(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. "Any Welfare" captures whether or not the individual had income from welfare programs such as TANF, general assistance, or other state and local programs. Observations are weighted using ACS individual sampling weights. Estimates are from a two-way fixed effects specification with 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 Program Income from American Community Survey

	SSA Income		SSI Income		Welfare Income	
	(1)	(2)	(3)	(4)	(5)	(6)
Uber in CBSA	-19.021***	-19.485***	-15.556***	-17.857***	-2.425	-1.393
	(5.337)	(5.931)	(3.541)	(3.697)	(1.969)	(2.105)
Demeaned Unemployment Rate		1.603		2.878**		2.354**
		(2.104)		(1.413)		(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. "Any Welfare" captures whether or not the individual had income from welfare programs such as TANF, general assistance, or other state and local programs. Observations are weighted using ACS individual sampling weights. Estimates are from a two-way fixed effects specification with 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 7: 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

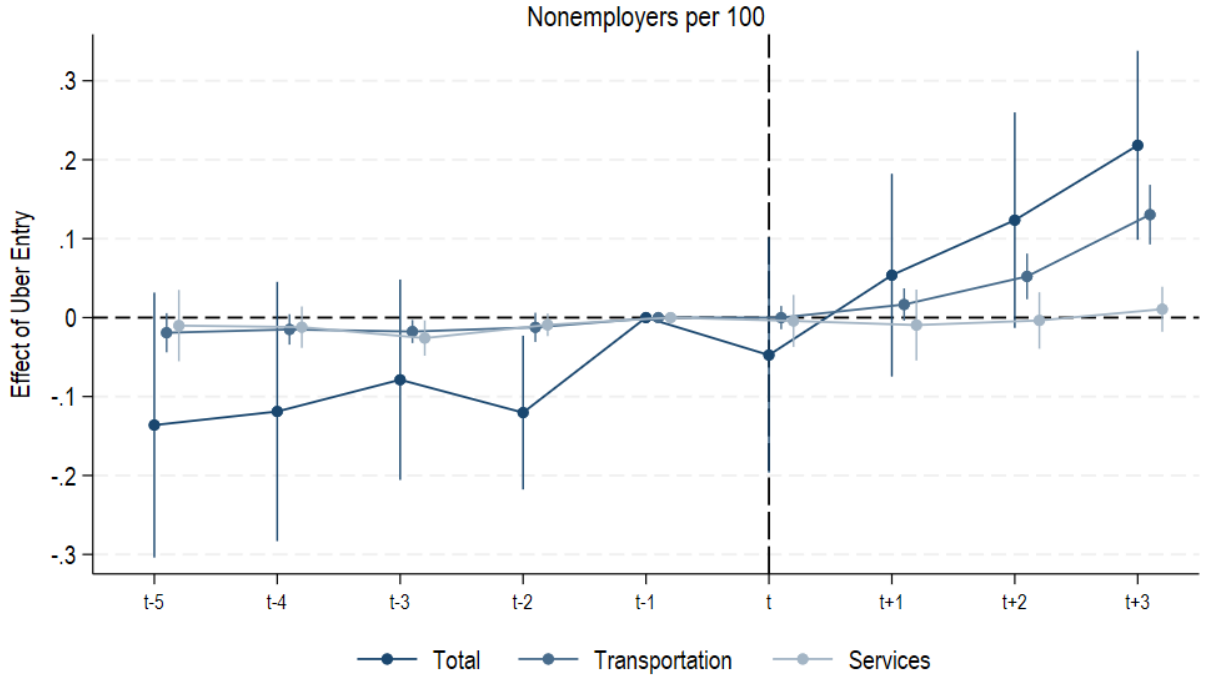
NOTE: Data come from matched SSA-HRS data from 1992 to 2020. Sample includes individuals aged younger than 70. Reported coefficients are from TWFE models as specified in equations (4) and (2). SSDI and SSI outcomes are derived from administrative SSA data. Observations are weighted using HRS individual 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. Estimates are from a two-way fixed effects specification with 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 8: 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*	-185.479	519.061***	-2.301	688.710***	-133.622	1368.084***
	(0.001)	(0.001)	(0.000)	(0.000)	(249.957)	(156.791)	(238.199)	(153.797)	(515.830)	(338.307)
Demeaned Unemployment Rate	0.728***	-0.006***	0.063***	0.000	4.4e+04***	-227.944**	3.9e+04***	-277.958***	9.5e+04***	-470.780**
	(0.001)	(0.001)	(0.000)	(0.000)	(112.270)	(112.422)	(106.989)	(103.685)	(231.689)	(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. Estimates are from a two-way fixed effects specification with metropolitan area and state-by-year fixed effects are included. Standard are clustered at the metropolitan area level. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *.

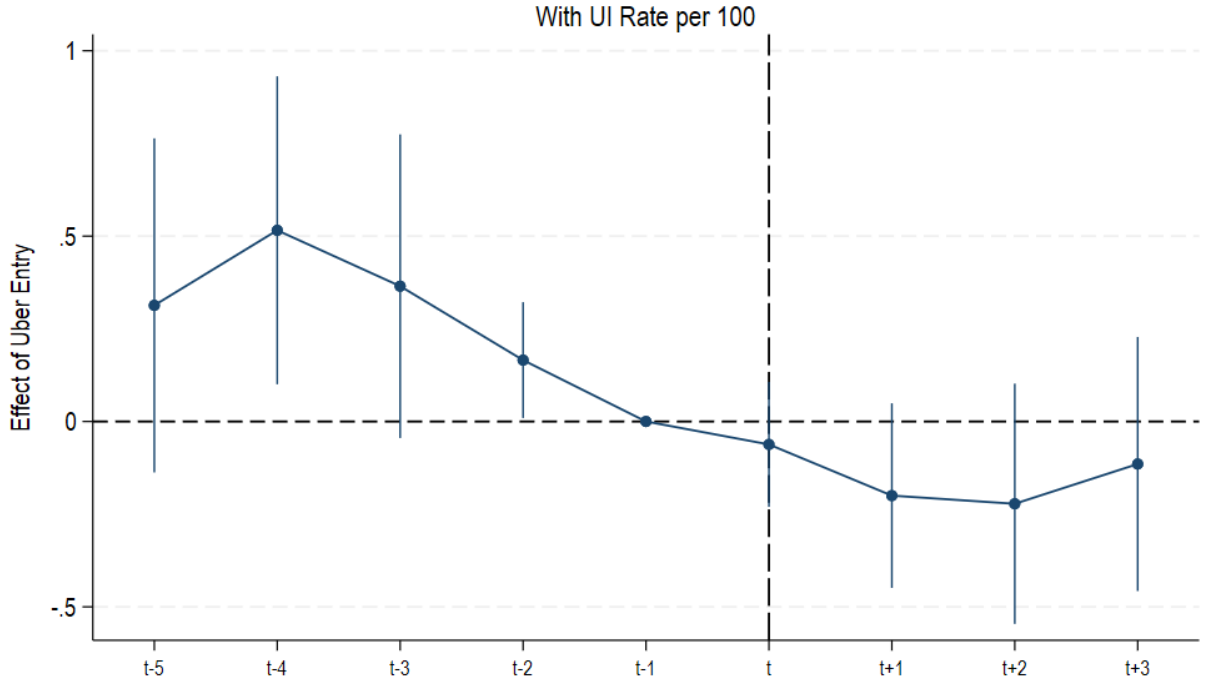
Figure A1: Stacked Event Study Effects of Uber Entry on Self-Employment



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. Estimates are from a stacked panel specification with 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.

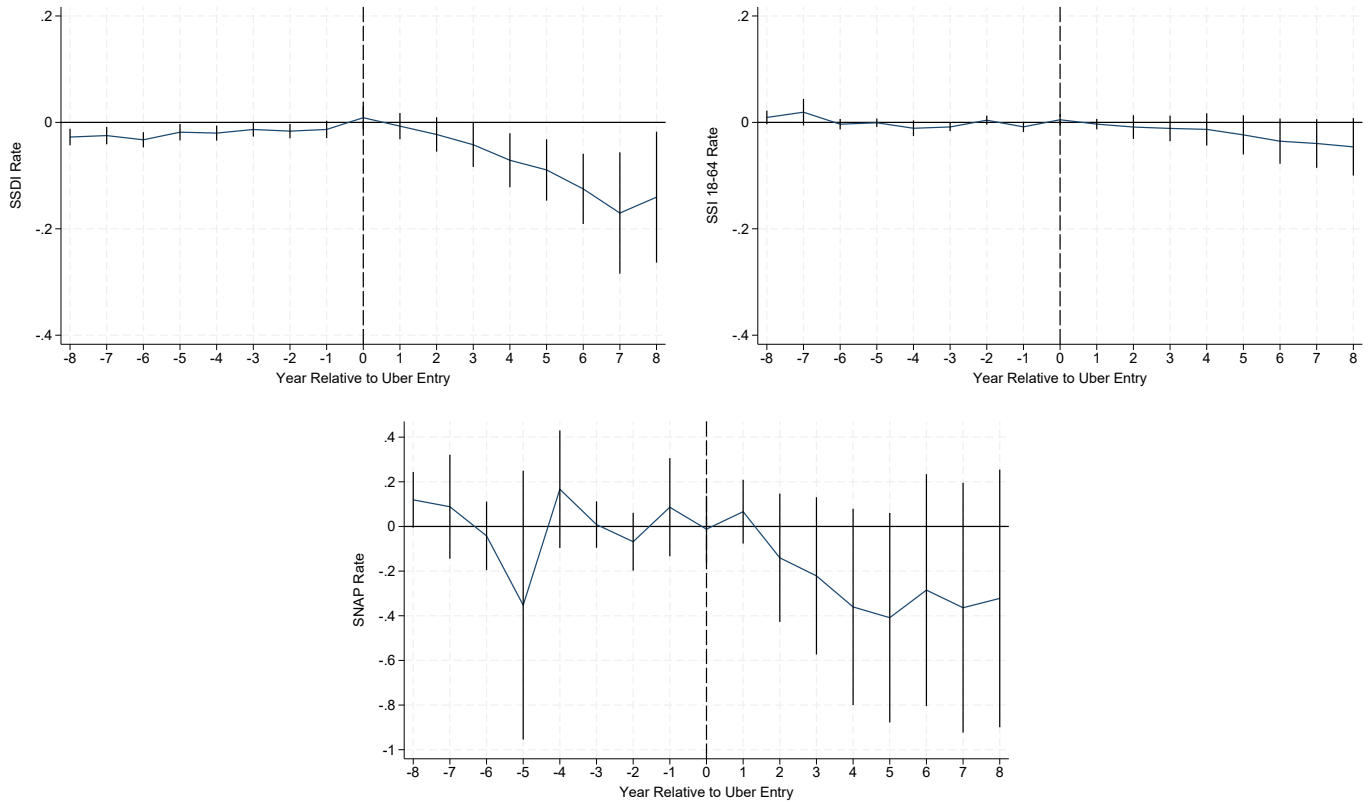
Figure A2: Stacked Event Study Effects of Uber Entry on Returns with Unemployment Insurance Income per 100



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. Estimates are from a stacked panel specification with 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.

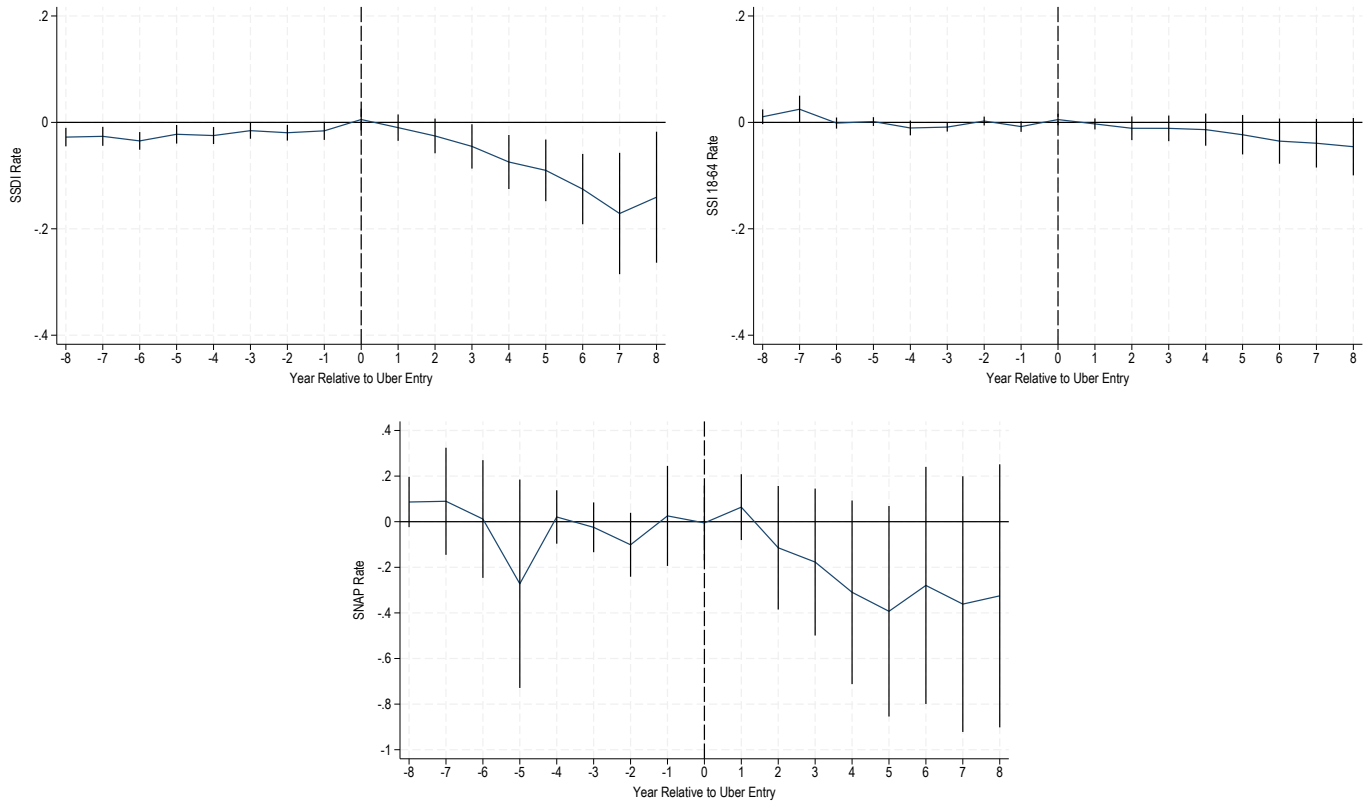
Figure A3: Doubly Robust Staggered-Timing Corrected Event Study Estimates of Uber Entry on County-level Program Caseloads: Not Yet Treated County Counterfactual



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.

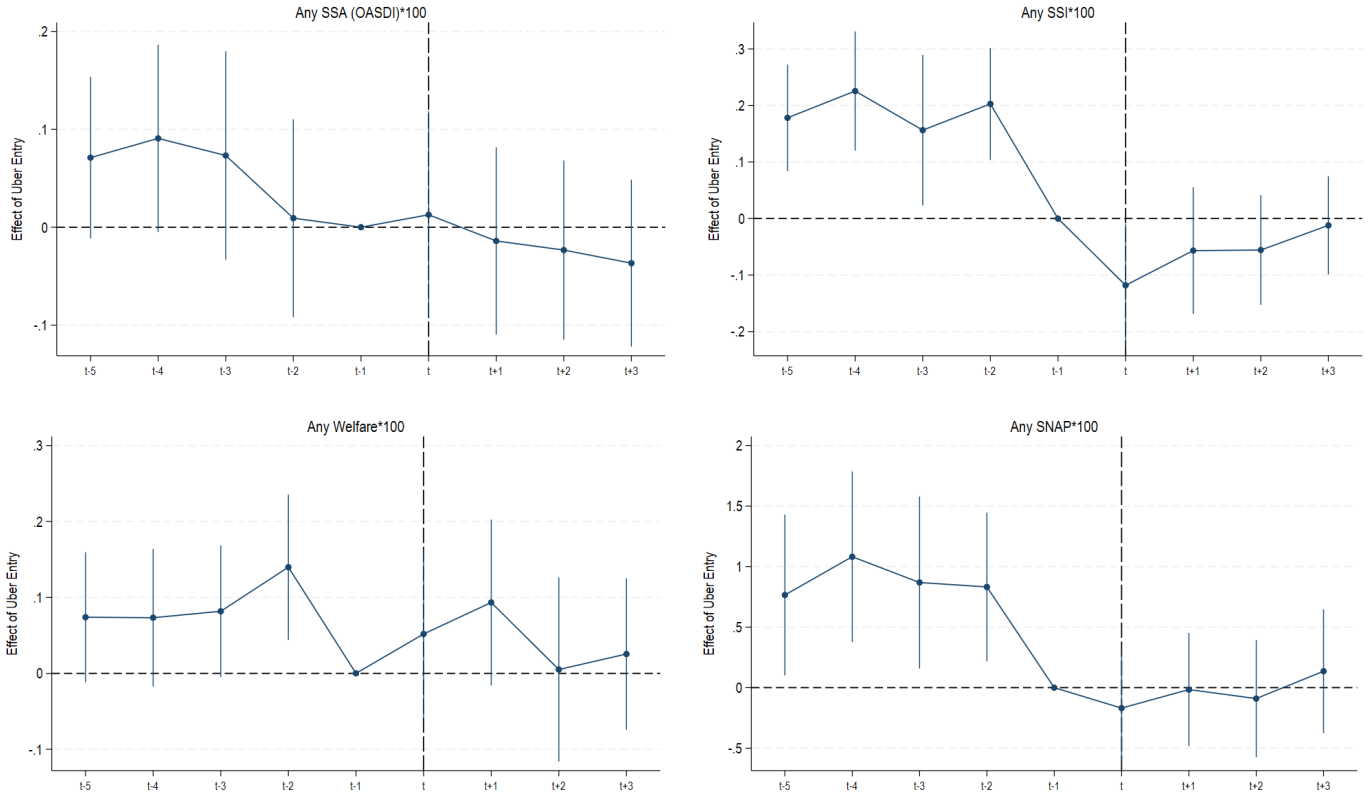
Figure A4: Doubly Robust Staggered-Timing Corrected Event Study Effects of Uber Entry on Program Caseloads: Never Treated County Counterfactual



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.

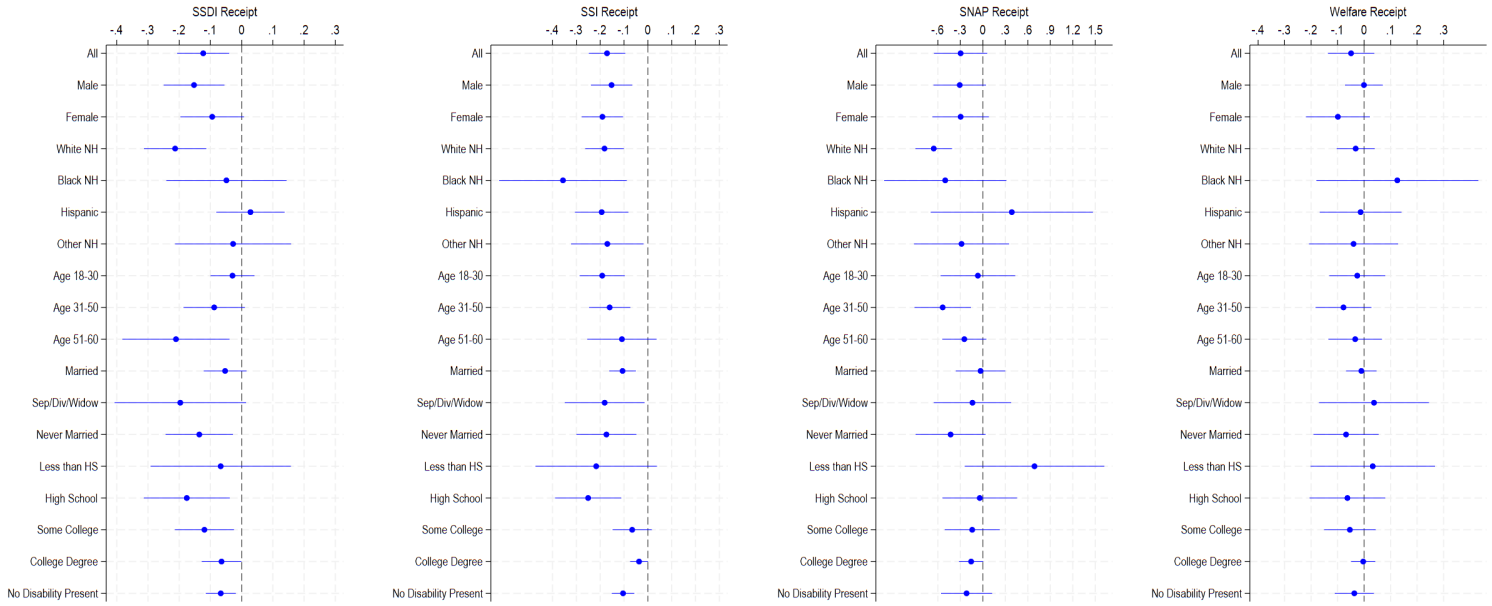
Figure A5: Stacked Event Study Effects of Uber Entry on Individual-level Participation from the ACS



NOTE: Estimates obtained from the stacked panel, where individuals (age 18-60) in metropolitan areas that gain access to Uber are compared to counterfactual individuals in metropolitan areas that obtain access to Uber four years later. As such, a individual 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 individuals in CBSAs are included. Estimates are from a stacked panel specification with 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 individual-level stacked panel from the 2005-2019 ACS.

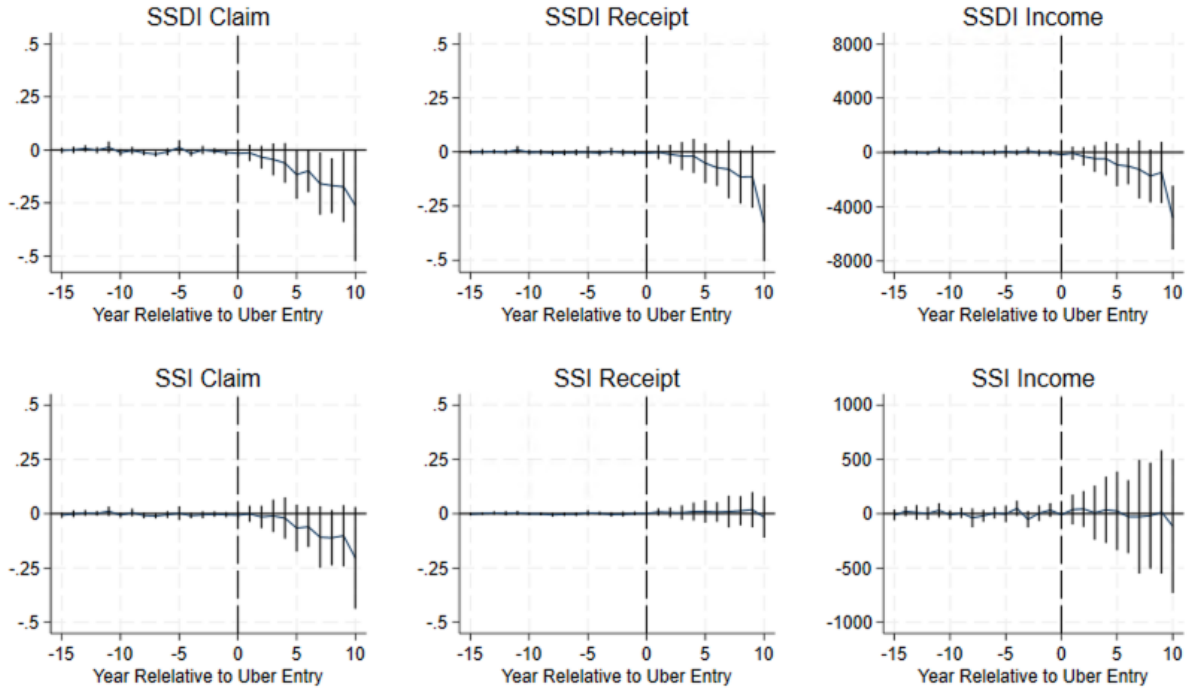
Figure A6: Heterogeneous Effects of Uber Entry on Program Participation



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 2005-2019 ACS.

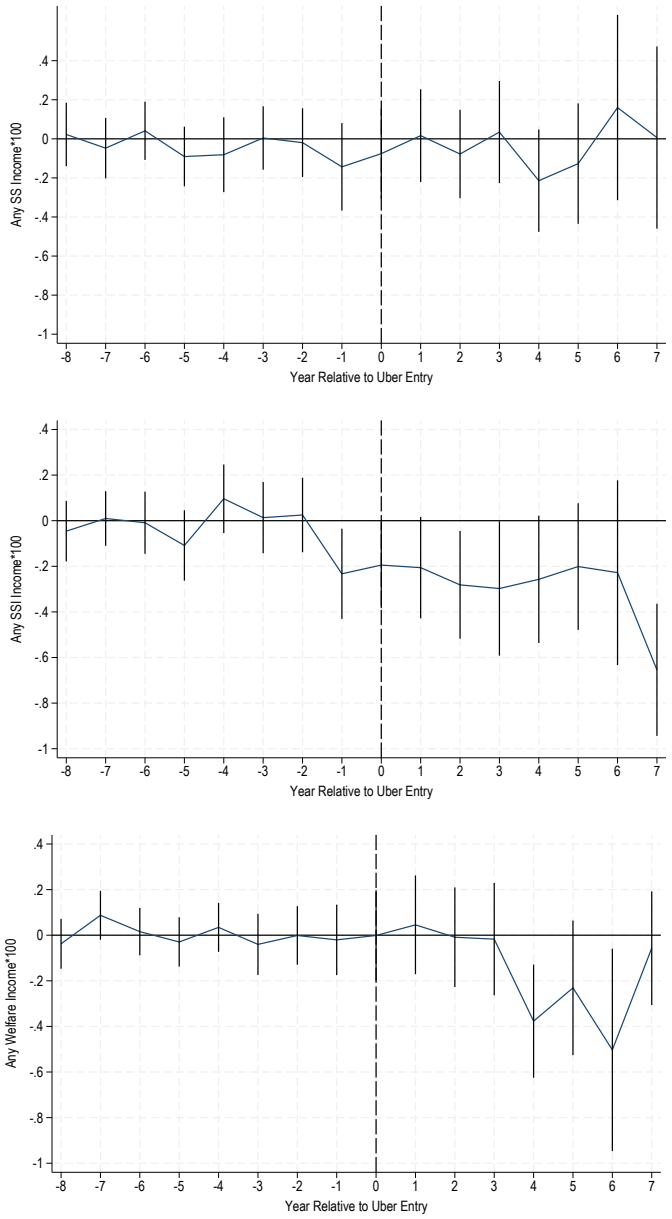
Figure A7: Doubly Robust Staggered-Timing Corrected Event Study Effects of Uber Entry on SSA Programs in HRS



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.

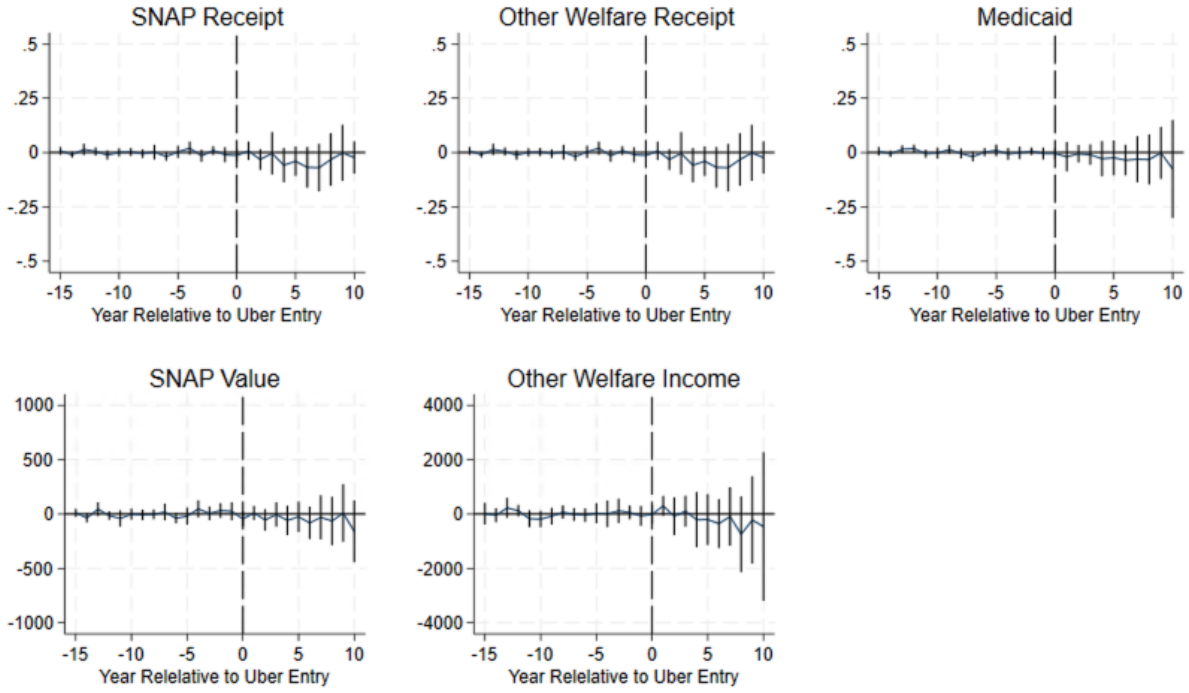
Figure A8: Staggered-Timing Corrected Event Study Effects of Uber Entry on Program Caseloads, ACS Aggregation



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 A9: 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: Effect of Access to Gig Opportunities on County-level Social Program Caseloads, Robustness to Unemployment Rate and Lagged Unemployment Rate

	SSDI Rate			SSI 18-64 Rate			SNAP Rate		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Uber in CBSA	-0.167***	-0.165***	-0.116***	-0.067***	-0.064***	-0.042**	-0.677***	-0.602***	-0.452***
	(0.024)	(0.025)	(0.025)	(0.019)	(0.019)	(0.019)	(0.137)	(0.134)	(0.135)
Demeaned Unemployment Rate	0.003			0.004			0.422		***
	(0.005)			(0.007)			(0.033)		
Demeaned Unemployment Rate t-1		0.038***	0.038***		0.015**	0.015**		0.468***	0.469***
		(0.006)	(0.006)		(0.007)	(0.007)		(0.038)	(0.038)
Uber in CBSA*Unemployment Rate t-1			0.059***			0.027***			0.199***
			(0.007)			(0.006)			(0.040)
Dependent Mean	5.16	5.16	5.16	2.57	2.59	2.59	12.48	12.76	12.76
Observations	30,518	30,518	30,518	34,105	32,311	32,311	27,847	26,340	26,340

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 A2: Effect of Access to Gig Opportunities on County-level Tax Returns with UI Income per 100 Adults

	Returns with UI Rate	
	(1)	(2)
Uber in CBSA	-0.144***	-0.005
	(0.040)	(0.050)
Demeaned Unemployment Rate		0.633***
		(0.021)
Uber in CBSA*Unemployment Rate		0.184***
		(0.017)
Dependent Mean	3.16	3.16
Observations	32,294	32,294

NOTE: Sample is restricted to counties during 2002, and 2004 to 2020 that are in CBSAs. Outcomes are measured as cases per 100 working age adults (18-64). 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. Estimates are from a two-way fixed effects specification with 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 A3: 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 A4: Stacked Panel Effect of Access to Gig Opportunities on Individual-level Program Participation from the ACS

	Any SSA (OASDI)*100)		Any SSI*100		Any Welfare*100		Any SNAP*100	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated*Post	-0.048***	-0.040**	-0.093***	-0.076***	-0.054**	-0.049*	-0.380**	-0.231
	(0.018)	(0.019)	(0.027)	(0.026)	(0.025)	(0.028)	(0.183)	(0.202)
Demeaned Unemployment Rate		0.011		0.005		0.060**		0.531***
		(0.017)		(0.018)		(0.026)		(0.107)
Treated*Post*Unemployment Rate		-0.004		-0.003		-0.001		0.025
		(0.008)		(0.008)		(0.009)		(0.050)
Dependent Mean	2.86	2.85	2.28	2.26	1.51	1.50	10.86	10.94
Observations	25,231,930	23,951,581	25,231,930	23,951,581	25,231,930	23,951,581	25,231,930	23,951,581

NOTE: Estimates obtained from the stacked panel, where individuals (age 18-60) in metropolitan areas that gain access to Uber are compared to counterfactual individuals in metropolitan areas that obtain access to Uber four years later. As such, a individual 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 individuals in CBSAs are included. Estimates are from a stacked panel specification with 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. Standard are clustered at the metropolitan area level. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *.

Table A5: 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 A6: 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 A7: 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 A8: 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 A9: 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 A10: 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 A11: 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 A12: 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 coefficients 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 A13: 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. Reported coefficients 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. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *.

Table A14: Robustness: Effect of Access to Gig Opportunities on Individual-level SSDI Participation - HRS data

	Panel A: Any SSDI Claimed					
	(1)	(2)	(3)	(4)	(5)	(6)
Uber in CSBA	−0.0259**	−0.0270**	−0.0232**	−0.0242**	−0.0026**	−0.0247**
	(0.0112)	(0.0119)	(0.0118)	(0.0118)	(0.0119)	(0.0118)
Demeaned Unemployment Rate		0.0008	0.0006	−0.00015		
		(0.0017)	(0.0017)	(0.0015)		
Uber × Unemployment Rate				0.0085***		
				(0.0028)		
Unemployment Rate_{t-1}					0.0008	−0.0002
					(0.0017)	(0.0016)
Uber × Unemployment Rate_{t-1}						0.0085***
						(0.0028)
Population Control	No	No	Yes	No	No	No
Dependent Mean	0.242	0.242	0.242	0.242	0.242	0.242
Observations	185,489	185,489	185,489	185,489	185,489	185,489
	Panel B: Any SSDI Received					
	(1)	(2)	(3)	(4)	(5)	(6)
Uber in CSBA	−0.0223***	−0.022***	−0.0199**	−0.0222***	−0.0224**	−0.0222***
	(0.0083)	(0.008)	(0.0083)	(0.0082)	(0.0084)	(0.0083)
Demeaned Unemployment Rate		0.00004	0.00007	−0.0001		
		(0.0011)	(0.0011)	(0.0011)		
Uber × Unemployment Rate				0.0013		
				(0.002)		
Unemployment Rate_{t-1}					0.00004	−0.0001
					(0.0011)	(0.0011)
Uber × Unemployment Rate_{t-1}						0.0013
						(0.0018)
Population Control	No	No	Yes	No	No	No
Dependent Mean	0.109	0.109	0.109	0.109	0.109	0.109
Observations	185,489	185,489	185,489	185,489	185,489	185,489

NOTE: Data come from HRS data from 1992 to 2020. Sample includes working individuals aged younger than 70. Reported coefficients are from TWFE models. All outcomes are self-reported in HRS data. Observations are weighted using HRS individual sampling weights. All models include demographic controls (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 A15: Robustness: Effect of Access to Gig Opportunities on Individual-level SS(D)I Participation - HRS data

	Panel C: Any SSI Applied					
	(1)	(2)	(3)	(4)	(5)	(6)
Uber in CSBA	−0.036***	−0.034***	−0.0299***	−0.034***	−0.0344***	−0.0339***
	(0.0100)	(0.010)	(0.0095)	(0.0099)	(0.0100)	(0.0099)
Demeaned Unemployment Rate		0.004***	0.0041**	0.0038**		
		(0.002)	(0.0016)	(0.0016)		
Uber × Unemployment Rate				0.0041*		
				(0.0022)		
Unemployment Rate$_{t-1}$					0.0008	0.0038**
					(0.0017)	(0.0016)
Uber × Unemployment Rate$_{t-1}$						0.0041*
						(0.0022)
Population Control	No	No	Yes	No	No	No
Dependent Mean	0.192	0.192	0.192	0.192	0.192	0.192
Observations	185,489	185,489	185,489	185,489	185,489	185,489
	Panel D: Any SSI Received					
	(1)	(2)	(3)	(4)	(5)	(6)
Uber in CSBA	−0.0017	−0.0012	−0.0022	−0.0013	−0.0018	−0.0014
	(0.0053)	(0.005)	(0.0051)	(0.0053)	(0.0053)	(0.0053)
Demeaned Unemployment Rate		−0.0003	−0.0003	−0.0006		
		(0.0009)	(0.0009)	(0.0009)		
Uber × Unemployment Rate				0.003**		
				(0.0012)		
Unemployment Rate$_{t-1}$					−0.0003	−0.0006
					(0.0009)	(0.0009)
Uber × Unemployment Rate$_{t-1}$						0.0030**
						(0.0012)
Population Control	No	No	Yes	No	No	No
Dependent Mean	0.124	0.124	0.124	0.124	0.124	0.124
Observations	185,489	185,489	185,489	185,489	185,489	185,489

NOTE: Data come from HRS data from 1992 to 2020. Sample includes working individuals aged younger than 70. Reported coefficients are from TWFE models. All outcomes are self-reported in HRS data. Observations are weighted using HRS individual sampling weights. All models include demographic controls (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 A16: Robustness: Effect of Access to Gig Opportunities on Individual-level Other Welfare Program Participation - HRS data

	Panel A: Any Food Stamps Received					
	(1)	(2)	(3)	(4)	(5)	(6)
Uber in CSBA	−0.0149*	−0.0143*	−0.0143*	−0.0141*	−0.0143*	−0.0157**
	(0.0081)	(0.0080)	(0.0081)	(0.0080)	(0.0080)	(0.0079)
Demeaned Unemployment Rate		0.0029***	0.0029***	0.0018*		
		(0.0011)	(0.0011)	(0.0011)		
Uber × Unemployment Rate				0.0065***		
				(0.0021)		
Unemployment Rate$_{t-1}$					0.0029***	0.0018*
					(0.0011)	(0.0012)
Uber × Unemployment Rate$_{t-1}$						0.0065***
						(0.0021)
Dependent Mean	0.072	0.072	0.072	0.072	0.072	0.072
	Panel B: Any Welfare Received					
	(1)	(2)	(3)	(4)	(5)	(6)
Uber in CSBA	−0.0167*	−0.016	−0.016	−0.0158	−0.016	−0.0177*
	(0.0100)	(0.0100)	(0.0100)	(0.0098)	(0.0099)	(0.0012)
Demeaned Unemployment Rate		0.0034***	0.0034***	0.0022*		
		(0.0012)	(0.0012)	(0.0012)		
Uber × Unemployment Rate				0.0076***		
				(0.0023)		
Unemployment Rate$_{t-1}$					0.0029***	0.0022*
					(0.0011)	(0.0012)
Uber × Unemployment Rate$_{t-1}$						0.0076***
						(0.0023)
Dependent Mean	0.113	0.113	0.113	0.113	0.113	0.113
	Panel C: Any Medicaid Enrolled					
	(1)	(2)	(3)	(4)	(5)	(6)
Uber in CSBA	−0.0099	−0.0097	−0.0102	−0.0095	−0.0097	−0.0113
	(0.0072)	(0.0073)	(0.0071)	(0.0072)	(0.0073)	(0.0071)
Demeaned Unemployment Rate		0.0031***	0.0031***	0.00005		
		(0.0007)	(0.0007)	(0.0010)		
Uber × Unemployment Rate				0.0070***		
				(0.0021)		
Unemployment Rate$_{t-1}$					0.0012	0.00005
					(0.0011)	(0.0010)
Uber × Unemployment Rate$_{t-1}$						0.0070***
						(0.0021)
Dependent Mean	0.074	0.074	0.074	0.074	0.074	0.074
	Panel D: Any Public Insurance					
	(1)	(2)	(3)	(4)	(5)	(6)
Uber in CSBA	−0.0285***	−0.0285***	−0.0242**	−0.0283***	−0.0285***	−0.0294***
	(0.0108)	(0.0108)	(0.0107)	(0.0107)	(0.0108)	(0.0109)
Demeaned Unemployment Rate		0.0004	0.0001	−0.0003		
		(0.0016)	(0.0016)	(0.0017)		
Uber × Unemployment Rate				0.0042		
				(0.0033)		
Unemployment Rate$_{t-1}$					0.0004	−0.0003
					(0.0016)	(0.0017)
Uber × Unemployment Rate$_{t-1}$						0.0042
						(0.0033)
Dependent Mean	0.398	0.398	0.398	0.398	0.398	0.398
Population Control	No	No	Yes	No	No	No
Observations	90,205					

Note: Data come from HRS data from 1992 to 2020. Sample includes working individuals aged younger than 70. Reported coefficients are from TWFE models. All outcomes are self-reported in HRS data. Observations are weighted using HRS individual sampling weights. All models include demographic controls (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 A17: Robustness: Effect of Access to Gig Opportunities on Individual-level SS(D)I Income - HRS data

	Panel A: SSDI Income					
	(1)	(2)	(3)	(4)	(5)	(6)
Uber in CSBA	−205.33	−206.06	−172.52	−201.53	−201.06	−201.38
	(139.17)	(139.36)	(137.38)	(137.54)	(139.36)	(138.09)
Demeaned Unemployment Rate		16.005	14.62	16.32		
		(17.531)	(17.48)	(17.94)		
Uber × Unemployment Rate				−2.78		
				(33.71)		
Unemployment Rate$_{t-1}$					16.01	16.32
					(17.53)	(17.94)
Uber × Unemployment Rate$_{t-1}$						−2.78
						(33.71)
Population Control	No	No	Yes	No	No	No
Dependent Mean	1,499.05	1,499.05	1,499.05	1,499.05	1,499.05	1,499.05
Observations	185,489	185,489	185,489	185,489	185,489	185,489
	Panel B: SSI Income					
	(1)	(2)	(3)	(4)	(5)	(6)
Uber in CSBA	−2.74	−2.35	−7.49	0.58	−2.35	−0.35
	(37.45)	(37.58)	(35.97)	(37.75)	(37.58)	(37.70)
Demeaned Unemployment Rate		1.77	2.06	−0.16		
		(6.03)	(6.09)	(5.65)		
Uber × Unemployment Rate				17.07*		
				(9.87)		
Unemployment Rate$_{t-1}$						−0.16
						(5.65)
Uber × Unemployment Rate$_{t-1}$						17.07*
						(9.87)
Population Control	No	No	Yes	No	No	No
Dependent Mean	225.28	225.28	225.28	225.28	225.28	225.28
Observations	185,489	185,489	185,489	185,489	185,489	185,489

Note: Data come from HRS data from 1992 to 2020. Sample includes working individuals aged younger than 70. Reported coefficients are from TWFE models. All outcomes are self-reported in HRS data. Observations are weighted using HRS individual sampling weights. All models include demographic controls (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 A18: Robustness: Effect of Access to Gig Opportunities on Individual-level SS(D)I Income - HRS data

	Panel C: Food Stamp Dollars					
	(1)	(2)	(3)	(4)	(5)	(6)
Uber in CSBA	−19.13	−17.73	−17.84	−17.62	−17.73	−18.58
	(14.45)	(14.31)	(14.48)	(14.34)	(14.31)	(14.14)
Demeaned Unemployment Rate		6.93***	6.96***	6.31***		
		(2.05)	(2.07)	(2.15)		
Uber × Unemployment Rate				3.84		
				(4.20)		
Unemployment Rate$_{t-1}$					6.93***	6.31***
					(2.05)	(2.15)
Uber × Unemployment Rate$_{t-1}$						3.84
						(4.20)
Population Control	No	No	Yes	No	No	No
Dependent Mean	125.86	125.86	125.86	125.86	125.86	125.86
Observations	90,205	90,205	90,205	90,205	90,205	90,205
	Panel D: Total Welfare Income					
	(1)	(2)	(3)	(4)	(5)	(6)
Uber in CSBA	−35.92	−32.99	−46.51	−33.23	−32.99	−31.13
	(100.51)	(99.18)	(97.48)	(99.11)	(99.18)	(99.90)
Demeaned Unemployment Rate		14.98	15.51	16.35		
		(15.39)	(15.46)	(15.86)		
Uber × Unemployment Rate				−8.39		
				(24.41)		
Unemployment Rate$_{t-1}$					14.98	16.35
					(15.39)	(15.86)
Uber × Unemployment Rate$_{t-1}$						−8.39
						(24.41)
Population Control	No	No	Yes	No	No	No
Dependent Mean	743.29	743.29	743.29	743.29	743.29	743.29
Observations	90,205	90,205	90,205	90,205	90,205	90,205

Note: Data come from HRS data from 1992 to 2020. Sample includes working individuals aged younger than 70. Reported coefficients are from TWFE models. All outcomes are self-reported in HRS data. Observations are weighted using HRS individual sampling weights. All models include demographic controls (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 A19: Robustness: Effect of Access to Gig Opportunities on Individual-level Other Outcomes - HRS data

	Panel A: Any Private Insurance					
	(1)	(2)	(3)	(4)	(5)	(6)
Uber in CSBA	0.0238**	0.0232**	0.0177	0.0232**	0.02315**	0.0230**
	(0.0109)	(0.0109)	(0.0110)	(0.0109)	(0.0109)	(0.0110)
Demeaned Unemployment Rate		−0.0031*	−0.0027*	−0.0032*		
		(0.0017)	(0.0017)	(0.0017)		
Uber × Unemployment Rate				0.0008		
				(0.0028)		
Unemployment Rate$_{t-1}$					−0.0031*	−0.0033*
					(0.0017)	(0.0017)
Uber × Unemployment Rate$_{t-1}$						0.0008
						(0.0028)
Population Control	No	No	Yes	No	No	No
Dependent Mean	0.688	0.688	0.688	0.688	0.688	0.688
Observations	90,205	90,205	90,205	90,205	90,205	90,205
	Panel B: Any IU Benefit					
	(1)	(2)	(3)	(4)	(5)	(6)
Uber in CSBA	−0.0008	−0.00013	0.0008	−0.0002	−0.0001	0.0003
	(0.0037)	(0.0037)	(0.0039)	(0.0037)	(0.0037)	(0.0037)
Demeaned Unemployment Rate		0.0032***	0.0032***	0.0035***		
		(0.0007)	(0.0007)	(0.0008)		
Uber × Unemployment Rate				−0.0018		
				(0.0011)		
Unemployment Rate$_{t-1}$					0.0032***	0.0035***
					(0.0007)	(0.0008)
Uber × Unemployment Rate$_{t-1}$						−0.0018
						(0.0011)
Population Control	No	No	Yes	No	No	No
Dependent Mean	0.034	0.034	0.034	0.034	0.034	0.034
Observations	90,205	90,205	90,205	90,205	90,205	90,205

Note: Data come from HRS data from 1992 to 2020. Sample includes working individuals aged younger than 70. Reported coefficients are from TWFE models. All outcomes are self-reported in HRS data. Observations are weighted using HRS individual sampling weights. All models include demographic controls (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. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *.