Availability of the Gig Economy and Long Run Labor Supply Effects for the Unemployed

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Abstract

A growing number of American workers earn income through platforms in the gig economy which provide access to flexible work (e.g. Uber, Lyft, TaskRabbit). This major labor market innovation presents individuals with a new set of income smoothing opportunities when they lose their job. I use US administrative tax records to measure take up of gig employment following unemployment spells and to evaluate the effect of working in the gig economy on workers' overall labor supply and earnings trajectory. To do so, I utilize penetration of gig platforms across counties over time, along with variation in individual-level predicted propensities for gig work based on pre-unemployment characteristics. In the short run, I show an increase in gig work following an unemployment spell and that individuals are correspondingly better able to smooth the resulting drop in income. However, individuals stay in these positions and are less likely to return to traditional wage jobs. Thus, several years later, prime-age (25-54) workers' income lags significantly behind comparable individuals who did not have gig work available. Among older workers (55-69), I find an increase in gig work corresponds to a reduction in receipt of Social Security Disability Insurance (SSDI). I shed light on mechanisms at play and show that either these individuals have extreme values for flexibility, and are outliers in their preferences, or individuals are perhaps procrastinating searching for a new job and not fully optimizing.

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1 Introduction

In the last decade, there has been a substantial increase in the number of individuals earning income through the "gig economy," by which I mean online platforms such as Uber or TaskRabbit.[1] As seen in Figure 1, the number of individuals with any gig work in the United States (US) increased from less than one thousand in 2007 to almost two million by 2016. This rapid emergence of the gig economy represents a potentially major change in the labor market, and presents workers with more flexible work opportunities.

I focus in this paper on the fact that gig labor market opportunities may be especially relevant for the unemployed population since they provide short-term, flexible work that permits workers to recover some of their lost income after job loss. This provides a new and valuable form of insurance while workers search for a job to re-enter the workforce. However, it is ultimately an empirical question as to whether short-term work in the gig economy – which may change individuals' job search behavior and delay (even indefinitely) their re-entrance into traditional employment – is beneficial in the longer term.

To investigate this issue, I quantify the take up of gig work following an unemployment spell and estimate the causal impact of participating in gig work on a workers' short-run and long-run earnings, employment, and education decisions. In doing so, I evaluate the trade-off between smoothing income in the short run and less attachment to traditional work in the long run, measuring the extent to which either or both are present. I utilize the universe of individual Federal income tax returns for the US and follow a panel of individuals who lose their job, which I measure based on one's receipt of unemployment insurance (UI).[2] I examine earnings, job type (e.g. gig versus wage employment), post-secondary school attendance, and social insurance receipt (e.g Social Security Disability Insurance (SSDI) and Social Security retirement) as they evolve before, during, and after job loss.

My empirical strategy leverages variation in gig platform availability across counties over time within the US that is driven by the geographic rollout of gig economy platforms. This exploits the fact that within a given county some individuals will have the additional option of working in the gig economy depending on the year in which they lose their job (i.e. those who lost their job after the entry of gig platforms). However, a simple difference-in-differences approach would not be able to disentangle the effects of gig availability from local labor-market changes happening differentially in places gig platforms entered earlier. This is potentially the case since platforms' decisions on where to enter first were largely driven by population, starting with highly populated areas, and larger cities may have recovered differentially from the Great Recession during the time

[1] The "gig economy" is used colloquially to refer to digital platforms that match consumers and providers. I focus on gig employment through online platforms rather than contract work more broadly.

[2] In the US, unemployment compensation is taxable income and therefore identifiable in the tax data.

period that I examine.[3]

To deal with this selective gig rollout, I incorporate within-area variation in individuals' predicted propensity for gig work by splitting individuals into two groups: high and low-gig-propensity.[4] In doing so, I account for local labor-market changes that affected all individuals within a county-year. For instance, high earners (prior to job loss) should not alter their behavior and so by accounting for the differences that they experience when gig platforms are available compared to when they are not helps me control for the possibility that outcomes are changing differentially in places where platforms entered earlier. I estimate a probit regression of the decision to ever participate in gig work on numerous pre-unemployment characteristics for individuals who had gig platforms available to them at the time of job loss. Utilizing these estimates, I identify comparable individuals who plausibly would have taken up gig work had it been available but simply did not have it as an option. I refer to these individuals as high-gig-propensity, and the remaining individuals as low-gig-propensity, excluding the bottom half of the propensity distribution as these individuals are less similar.

This technique yields a high-gig-propensity group that is 18 percentage points more likely to engage in gig work than the identified low-gig-propensity workers, among individuals with the most gig availability relative to no gig availability. Prior to losing their main job and receiving UI, essentially no individuals were working in the gig economy to any degree.[5] Following job loss, I document an extensive-margin increase in gig work. Among the overall sample of UI recipients, about 1-2% of individuals take up gig work following an unemployment shock.

Combining variation in gig availability and individuals' propensity for gig work, I estimate a triple-difference specification that estimates the impact of gig availability following job loss (Gruber, 1994). I establish three main findings. First, high-gig-propensity individuals with the highest degree of gig availability experience a short-term benefit in income relative to those without gig availability. Their individual and household income drop by \$3,000 less in the year of UI receipt than those without gig platforms available. However, the income of those without gig availability catches up the year after UI receipt.

Second, I find that despite a smaller drop in income in the short run, two to four years later the income of prime-age workers who had gig platforms available when and where they lost their

[3] Population has an R squared value of 0.75 in predicting the year that gig platforms enter a county. This R square comes from a simple regression of the year of gig entry on 2014 county population as a cubic to pick up the curvature of the relationship.

[4] Similar methodology has been employed in other papers, e.g. Banerjee et al. (2018) use within area variation in individuals likelihood of taking up microfinance and compare individuals with high and low propensity for microfinance in villages that do and do not receive microfinance as an option.

[5] This is partly by construction as all of these individuals must have started with a traditional wage job in order to lose it. However, as I show with co-authors in Collins et al. (2019), the majority of workers in the gig economy overall are actually individuals who hold a main wage job and gig work is a secondary source of earnings.

job begins to lag significantly behind those who did not have gig platforms available, and this is driven by lower wage earnings. I show that individuals without gig availability begin to return to wage jobs, while individuals with gig availability stay in gig positions and are five percentage points less likely to return to traditional wage jobs two to four years after UI receipt. This translates into $4,000 lower wage earnings and household income, relative to their high-gig-propensity counterparts without any gig platforms available.

Third, I establish important heterogeneity across ages by differentiating between prime-age workers (ages 25-54) and older workers (ages 55-69), as older individuals have been shown to highly value flexibility (Ameriks et al., 2017) and are especially vulnerable after losing their job.[6] Crucially, the implications of entering into gig work depend on the set of relevant and available options following job loss for each age. Empirically the outside options differ dramatically for these two age groups. For prime-age workers, gig work crowds out wage jobs that provided higher earnings as well as important employer-sponsored benefits. In contrast, for older workers, gig work prolongs labor force participation. An increase in gig work instead reduces receipt of Social Security Disability Insurance (SSDI) benefits and may delay claiming of Social Security retirement benefits, which can be financially advantageous.

This study helps to distinguish among mechanisms that are consistent with the observed patterns for prime-age workers. First, it may be that individuals learn that they value flexibility after entering into gig work. Alternatively, individuals may have time-inconsistent preferences, and plan to search for a new job yet keep procrastinating. Estimates I find imply that individuals are willing to forgo 39% of their earnings in exchange for flexibility. To rationalize the pattern of observed earnings, individuals would need to have a small discount factor, no larger than 0.86. Together these estimates suggest that either these individuals have extreme values for flexibility, and are outliers in their preferences, or individuals are perhaps procrastinating searching for a new job and not fully optimizing. In fact, both may be at play, and policy intervention would be beneficial to mitigate behavioral issues if they are at play.

This paper relates to a large theoretical and empirical literature on the behavior of the unemployed. In particular, the gig economy provides a new option for individuals during this time. The key contributions that I make in this paper are quantifying takeup of gig work following an unemployment shock, evaluating its ability to help buffer the drop in income, and estimating the long-run consequences of this takeup for earnings, employment, and skills acquisition.[7] This has

[6] Ameriks et al. (2017) show that among older workers, willingness to work longer is higher for jobs that offer flexible schedules and demand-side factors (such as the availability of such flexible positions). Additionally, several papers examine bridge jobs, which individuals use to partially retire (Maestas, 2010; Rubert and Zanella, 2015; Ramnath et al., 2017).

[7] In particular, there are several key mechanisms that research has examined in the context of unemployment that relate to this paper: duration (Moffitt, 1985; Katz and Meyer, 1990a; Chetty, 2008), search intensity (Mortensen, 1977), reservation wages, consumption smoothing (Gruber, 1997), spousal labor response (Cullen and Gruber, 2000) and job

parallels as well to prior work examining the impacts of experience at temporary help agencies on subsequent labor market outcomes (Autor, 2001; Autor and Houseman, 2010; Pallais, 2014).

Second, this research builds on an emerging but rapidly growing literature that seeks to understand the recent growth of the gig economy and alternative work arrangements, more generally.[8] Relatedly, Katz and Krueger (2017) show with survey data that unemployment is a strong predictor of alternative work transitions. Farrell et al. (2019) document bank account income declining steadily and involuntary job loss events preceding increases in online platform participation and revenues. While we now have a grasp on the growth of this type of work, very little is yet known on the impact of participating in these positions on labor-market outcomes.[9] My key contribution is providing evidence on the causal effects of working in the gig economy following job loss, on short and long-run labor-market outcomes.

Additionally, this relates closely to many studies that highlight the importance of examining how the flexibility provided by gig work attracts workers.[10] In fact, many drivers cite their preference for flexibility as the reason why they work for Uber (Hall and Krueger, 2018). This paper also complements Koustas (2018), who shows that rideshare income helps drivers smooth consumption when facing income fluctuations in their primary job. A key contribution of this paper is to investigate long-term outcomes associated with partaking in gig work, specifically for those who enter gig work following an unemployment shock.

This paper proceeds as follows. In Section 2, I provide details on the data and sample construction as well as summary statistics. I then present descriptive evidence on how outcomes evolve dynamically before and after job loss in Section 3. I explain and motivate my empirical approach in Section 4. In Section 5, I present my main results for prime-age and older workers. I provide evidence on robustness in Section 5.3. A discussion of these results is included in Section 6. Finally, I conclude in Section 7.

matches (Acemoglu and Shimer, 1999; Acemoglu, 2001).

[8]Early efforts to measure gig work use data from a variety of sources, including: surveys, financial institutions, google trends, and private employers. Estimates indicate that roughly 0.4-1.6 percent of workers are involved in the gig economy (Harris and Krueger, 2015; Farrell and Greig, 2016; Farrell et al., 2018; Katz and Krueger, 2019), and that the percentage of workers engaged in alternative work arrangements and contract work is increasing more broadly (Jackson et al., 2017; Collins et al., 2019; Katz and Krueger, 2019). In earlier work, we show that most of the growth in self-employment appear primarily to be providing labor services as contractors or freelancers (Jackson et al., 2017) and is largely being driven the by the growth in gig work mediated through online platforms (Collins et al., 2019).

[9]Other studies have examined the effects of Uber or gig availability on the gender gap (Cook et al., 2019b), older workers (Cook et al., 2019a), auto financing (Buchak, 2019), and loan delinquency and credit utilization after being laid off (Fos et al., 2019).

[10]Though many workers are not willing to pay for schedule flexibility, there exists a long tail of workers with high willingness to pay (Mas and Pallais, 2017). Additionally several papers have examined the value of flexibility as a job amenity or attribute (Goldin, 2014; Maestas et al., 2018; Wiswall and Zafar, 2018).

2 Data, Sample Construction, and Summary Statistics

2.1 Individual Income Tax Returns

I use the universe of individual income tax returns filed in the United States from 2005-2017, which include both income tax returns that are filed by individuals aggregating all of their earnings and deductions (e.g. Form 1040, Schedule C), and third-party information returns that are filed by employers or payers on behalf of the payee denoting the amount of money transferred between the two entities (e.g. W-2s, 1099s). Taken together, these forms contain a wealth of data on: demographic and economic characteristics, sources of earnings, benefit coverage, and receipt of social insurance.

Key advantages of these data are the panel nature, which allows me to track individuals over time, and the comprehensive scope that identifies both the sources and concentration across sources of an individual's earnings. Crucially, I am able to differentiate between traditional wage employment and self-employment, and separately identify employers or payers from whom they received payments.[11] As this is administrative population-level data on the self-employed and gig work population, this addresses many shortcomings of other data sources, which often focus on particular samples, primary employment, or a snapshot in time. This is of particular importance as recent research has shown that survey-based measures appear to underestimate self-employment Katz and Krueger (2019); Abraham et al. (2018).

However, these data are designed for tax administration purposes. Thus, the data only contain the necessary information for an individual to compute and file their taxes, and for the government to monitor tax compliance. For example, the data contain aggregate annual earnings from each employer, but do not decompose the earnings further into hours or a wage rate.

Geography I use counties as the level of geography in my analyses and this is the level for which I define the local labor market. The data identify individual addresses including ZIP code which I map to counties. Individuals typically file and/or receive multiple tax forms in a given tax year, each of which do not necessarily contain the same ZIP code. Thus, for the subset of individuals for whom I identify multiple ZIP codes in a given year, I use the ZIP code that they denote on their individual tax return (Form-1040) if they filed their taxes.[12] For non-filers, I use the modal ZIP code denoted on all information returns that they received.

Demographics Individual demographics include age and gender, and are retrieved from ta-

[11] It is worth noting that not all self-employed individuals will have work that is firm facing but for those who do, they would receive a Form 1099 from that firm. However, for those who do not interact with a firm or payer we would not expect a Form 1099.

[12] In cases where the ZIP code on an individual tax return is incorrect or missing, I use the modal ZIP code from other tax forms filed by an individual (e.g. Schedule C), if valid. Otherwise, I use the modal ZIP code denoted on all information returns received by an individual.

bles obtained by the IRS from the Social Security Administration (SSA). More precisely, the data contain each individual's date of birth. I construct age as the tax year minus birth year.

Household Structure In years that individuals file their taxes, for married individuals I can match them with their spouse with their individual tax return (Form-1040).[13] Similarly, I identify the number of children that individuals have based on the number of child dependents they claim (on Form-1040) in that year.

Social Insurance In addition to measures of income, tax information returns contain details on social insurance receipt. Precisely, I identify the receipt of unemployment compensation (1099-G), Social Security Disability Insurance (1099-SSA), and Social Security Retirement benefit withdrawal (1099-SSA).

2.2 Measuring Gig Work and Availability

I identify individuals who provide services through online gig platforms based on the receipt and/or filling of a variety of tax forms, and irrespective of the tax filing status of that individual. More specifically, I utilize information returns (Form 1099-MISC and Form 1099-K) that are distributed from platforms to workers, and returns filed by an individual denoting self-employment income (Schedule C).[14]

I identify individuals who work for gig platforms by those who receive a 1099-K or 1099-MISC from a gig platform Employer Identification Number (EIN), and based off their self-described business professions on Schedule C. It is important to note that Forms 1099-MISC and 1099-K are not used solely for the online platform economy; similarly, individuals file Schedule C to report income earned from a plethora of sources. Appendix B discusses these forms and their uses in more details.

Based off publicly available lists, I include approximately 50 large online gig platforms for whom workers provide labor based work to be apart of the "gig economy" definition.[15] As noted in Farrell et al. (2018), the majority of platform work is made up of transportation platforms. For each labor platforms, I identify all individuals who receive a 1099-MISC and/or 1099-K from that firm. I consider these individuals to have gig work. Additionally, individuals reporting compensation related to one of these platforms, or gig work more broadly, are also included for reasons discussed in Appendix B.

[13]This is true if their filing status is "married filing jointly" or "married filing separately".

[14]Information returns are sent from platforms to the IRS regardless of whether an individual ultimately files their taxes.

[15]This definition of online gig platform work can be viewed as an underestimate of the gig economy. Nonetheless, it provides extensive coverage of individuals working for major platforms in the sector, and thus works well in terms of capturing individuals propensity for gig work. Further, given that filing thresholds appear to not be binding in practice during this time period, there are not concerns in censoring of the earnings distribution among gig workers.

Gig Availability by County

I construct a measure of gig availability at the county-by-year level utilizing the prevalence of gig work as identified at the individual level. I aggregate the number of individuals that I observe in each county-by-year cell with any amount of gig work, and identify the first year of gig availability to be the first year in which I observe at least 30 individuals in that county with gig income.[16]

Appendix Figure A3 highlights the variation across counties over time in the availability of gig work as defined by this measure. There are two key takeaways from Appendix Figure A3. First, each year more counties have gig platforms available as an option, indicated by more polygons being shaded. Second, gig platforms are also becoming more prevalent within each county over time, indicated by the shading of each polygon shifting from a light beige towards a darker red.[17] Gig platform work may be increasing in prevalence over time, within an area, for many reasons. For instance, this measure includes multiple platforms and thus once one platforms enter others likely follow suit. Additionally, supply and demand for platforms will grow with local knowledge of platforms and their services.

2.3 Sample Construction

Pulling together the components of the data described above, I construct my analysis sample to consist of individuals experiencing involuntary periods of unemployment as identified by receipt of unemployment compensation.[18] I draw my sample from the population of individuals with any positive unemployment compensation in the years 2008-2015. Additionally, I utilize data from 2005-2017 for each individual which provides a sample that is balanced in event time over the period three years pre- and post-UI receipt (including the first year of UI receipt).

The final analysis sample includes an individual's first new UI claim between 2008 and 2015. UI events are restricted to counties that gig platforms enter by 2015. There are 23 million prime-age workers and 5 million older workers who experience an UI event in my final analysis sample, from which I draw my stratified random sample. This leaves 917,128 prime-age workers and 106,243 older workers after stratification. See Appendix B.3 for more details on each data restriction and sampling methodology.

[16] I utilize a cutoff of 30 individuals in a county-by-year cell for disclosure reasons at this geographical level.

[17] Note that the legend is the same across each sub-figure to facilitate comparison across years.

[18] I only observe eligibility for unemployment compensation conditional on take-up of benefits, and not the full set of individuals who were eligible but chose to not apply. Given the scope of the tax data, there are limited alternative ways to identify individuals experiencing a period of involuntary unemployment, and the main alternative would be to examine mass layoffs. See Appendix C for further discussion of UI takeup.

2.4 Variable Definitions

I construct several key outcome variables that together encapsulate the implications for employment, earnings, education, and access to various benefits. All years I use are tax years which correspond to calendar years.

Gig Work and Gig Earnings Gig work is an indicator for whether or not I identify an individual with any gig work in a given year, as I described above. Gig earnings represent gross receipts, as reported by the platforms on Form 1099-MISC and 1099-K, and do not account for the associated business expenses that an individual deducts. I observe the amount of business deductions that an individual claims in a given year (on the return Schedule C), and thus also identify self-employment income net of business deductions. My measure of income that I describe next accounts for all business deductions claimed by an individual.

Individual and Household Income I use two different measures of income: one at the individual-level and another at the household-level. I can only identify household-level income for filers when I can link individuals together with their spouse based off their filing on the Individual Tax Return (Form 1040). Household-level income I define as the household's adjusted gross income (AGI) as reported on Form 1040. Since I also observe income for non-filers, I construct a second income measure to incorporate this additional information.[19] For individual income, for filers I assign half of the household's adjusted gross income for married individuals and all of AGI for non-married filers, and for non-filers I aggregate income reported on information returns which include wage earnings (Form W-2), unemployment benefits (Form 1099-G), and social security and disability benefits (Form SSA-1099).[20] As a robustness, for both measures of income I utilize only the summed information return values rather than AGI.

Labor Force Participation I examine labor force participation across three different types of employment: traditional wage employment, gig employment, and self-employment more broadly. For each employment type, I evaluate both the extensive margin, measured as a dummy variable indicating any amount of employment of that type, and the intensive margin, measured in earnings. Unfortunately, I do not have data on hours, months or days worked during the year so I cannot break these earnings apart into an hourly or monthly rate, and thus can only look at aggregate earnings.

SSDI and Social Security Retirement Benefits I construct a variable that identifies the amount of social security benefits received in a year, as denoted on Form 1099-SSA. I differentiate between benefits received from the retirement fund versus disability fund.

Post-Secondary Attendance I identify if an individual is a student at a college, vocational

[19] Importantly, the individual income measure should be immune to differential changes in filing behavior from gig availability or take up, that may be present with the household-level income for which I have to restrict to the subsample of filers.

[20] Prior to 2007, due to data limitations, self-employment income cannot be separately allocated to individuals within a household and thus this allows for consistency over time in the definition of individual income.

school or other post-secondary institution by receipt of Form 1098-T in a given year. All institutions eligible for the Department of Education's student aid programs must issue this form to all students and the IRS, which identifies all qualified education expenses.

2.5 Summary Statistics

In Table 1, I present summary statistics for the entire analysis sample described in Section 2.3. An observation is an individual-year, and summary statistics are presented for pre-UI receipt years in the balanced sample restricted years —the three years prior to UI receipt.

As seen in Table 1, the majority of my sample are filers, 91%. 30% of the sample is female and on average individuals are 33 years old. Among the 91% who filed, household AGI is on average $45,997 and the median household income is $34,500.[21] Individual income is on average $31,920 and almost entirely attributable to wages which are on average $33,204.[22] Additionally, the individual is typically the primary wage earner within the household, as spouses' wages are on average $8,362 relative to the individual's wages, $33,204.

On average over the three years prior to unemployment, 91% held a wage job. As seen in Figure A1 the share with a wage job is increasing over the three years prior to UI receipt. This is high by construction, as to receive UI the individual must have first held a wage job from which to become unemployed and eligible for UI.[23] Additionally, 15% of households filed Schedule C for income earned in a sole proprietorship —this includes individuals who earn income as an independent contractor or small business owner, for example. 17% were enrolled at a post-secondary institution. As a baseline, about 0.30% held a gig position in the pre-UI period.

To help put these numbers in context, compared to the overall wage earning population, these individuals are on average younger, less likely to be married, and have lower household AGI. For example, the median household income in the US in 2017 was $61,372, and $55,000 (in 2017 $) back in 2010.[24] On the other hand, the median household AGI among this sample, $34,500, is substantially lower. As a result, a slightly higher number of these individuals, 23%, live in households that claimed the EITC.

[21] I winsorize the top and bottom 1% of income values. Large outlying negative values of AGI typically represent large claimed losses. The top 1% of wage values are also winsorized.

[22] There are a number of reasons why on average wages are slightly higher than individual income. First, a component of individual income is AGI, which accounts for specific deductions. Second, is if the household has any reported business losses then that would reduce the overall AGI. Third, is by the construction of the individual income variable - if the individual is in a married household and earns the majority of the household income from his or her wages, then when that is divided by the number of two that may be less than his or her wages.

[23] Note, an individual may have lost their job at time -1 or 0, and thus we wouldn't necessarily expect to have 100% wage job share in either year.

[24] Median household income in 2017 was sourced from https://www.census.gov/library/publications/2018/demo/p60-263.html. Median US household income in 2010 was $49,445 and adjusted to 2017 dollars (https://www.census.gov/newsroom/releases/archives/income_wealth/cb11-157.html).

3 Descriptive Evidence on Behavior around UI Receipt

Figures A1 and A2 illustrate how each key outcome variable typically evolves, on average, dynamically relative to the year of UI receipt. These values are restricted to individuals without gig availability to provide a baseline comparison of magnitudes for subsequent analyses. I describe outcomes for prime-age workers in Figure A1 and older workers in Figure A2.

Prime-Age Workers

On the extensive margin, measured as indicator for having any gig work in a given year, participation in gig work prior to job loss is effectively zero, which is by construction given that these individuals at the time of UI receipt live in a county without gig platforms yet available.[25] Even by four years after after UI receipt, only 0.4% of individuals have any gig work compared to 2% of those who had gig platforms available.

Prior to job loss, household AGI is on an upward trajectory and increases on average from $40,000 to $49,000. However, households experience a drop of almost $5,000 in the year of UI receipt and the following year before starting to recover. Similarly, individual income drops from about $35,000 to $29,000, and begins to recover two years after UI receipt. Underlying these drops in income are decreases in wage earnings corresponding to the job loss prompting UI receipt.

An individual's annual wage earnings combine two margins of variation: the extensive margin, whether an individual holds a wage and salary job, and conditional on having such a position, how much do they earn in annual earnings. On average, individuals are more likely to hold a traditional wage and salary position over time prior to the job loss incident of interest. This rate increases from 87% to 95% of individuals in the years leading up to UI receipt. Recall, by construction, all of these individuals must have held a wage job at least once in the years prior to the job loss I identify in order to be eligible for UI. In the year after UI receipt, only 78% of individuals without gig availability have a wage job, this is a sharp drop of 17 percentage points. Two years following UI receipt we see an increase of about 5 percentage points in likelihood of holding a wage job, indicating that roughly one-third of individuals are able to return to the work force. However, this share stays relatively constant and does not appear to increase substantially over time following the initial increase.

Corresponding to the job loss timing and the patterns we see with the extensive margin of holding a wage job, wage earnings increase from about $27,000 to $37,000 prior to UI receipt. In the year of UI receipt, wage earnings drop to about $27,000 and bottom out at $23,000 the year

[25] It is possible that individuals move over time and thus since I have defined gig availability for each individual to be in the year and county of UI receipt, some individuals may have lived in an area with gig platforms prior to the year of UI receipt; for this reason, these means are not necessarily precisely zero. However, we see that this is very uncommon, and individuals appear to have essentially no gig work prior to job loss.

following UI receipt before starting to recover on a trajectory similar to that prior to job loss.

The spouse of the individual facing job loss earns about $9,000 prior to the individual's job loss and this is relatively stable, though growing slightly, over the years leading up to UI receipt. Following job loss, we observe a clear spousal labor response given a shift in slope of zero to a positive slope of wage earnings. This indicates that, on average, an individual's spouse is contributing more to the household income following the unemployment shock.

On average, about 19% of the individuals are enrolled in post-secondary institutions with eligible tuition payments five years prior to job loss. This is trending downward leading up to job loss, as individuals are less likely to still be in school as they age. There is a clear break in trend and a small increase of about 1 percentage point in schooling in the two years surrounding job loss, before continuing to decrease on the same trend as prior to job loss.

Older Workers

In Figure A2, there are some key differences in the patterns exhibited among older workers exhibit as compared to prime-age workers. First, household AGI and individual income are on average higher at baseline prior to job loss and relatively stable. This is not surprising as these individuals are older and later in their career. On average, they experience a larger drop in income and household AGI, $10,000, compared to prime-age individuals whose income dropped by about $5,000.

Second, there is a substantially larger drop in the share of individuals holding a subsequent wage job following job loss, almost 30 percentage points. Additionally, unlike the pattern exhibited by prime-age workers in A1, there is not a small recovery in the rate of individuals holding wage jobs in the years following UI receipt. Finally, we see an increase in the share of individuals with the receipt of SSDI benefits that corresponds to the timing of UI receipt. Prior to job loss, the share with the receipt of SSDI benefits is steady at about 2%. Starting the year of UI receipt, we see the share with any receipt of SSDI benefits increase from 2% to 10% four years later. There is a similar pattern with the share of individuals claiming social security retirement benefits; though this is trending up more prior to job loss and so does not exhibit as pronounced of an increase following job loss but rather a change in slope.

4 Empirical Approach

The ideal experiment to identify the causal effect of taking up gig work following an unemployment shock would be to randomly assign individuals into and out of gig work at the time of the unemployment shock. The difference in the outcomes between the two groups would identify the treatment effect of taking up gig work, as well as the dynamics of these effects. However, in practice there is presumably non-random selection into gig work after an unemployment shock. For instance, selection might depend on how large or small of an income shock the individual is faced with, how likely the individual is to get another wage job, which might be a function of their prior industry or experience, or their ability to recover lost earnings through other responses (e.g. spousal labor response).

Since the primary objective of this paper is to identify the causal impact of taking up gig work during spells of unemployment on individual's outcomes, I need exogenous variation in take up of gig work to provide a valid counter-factual behavior during unemployment. To address this, my empirical approach leverages two key sources of variation: the availability of gig platforms and individual's propensity for gig work. First, I exploit geographical variation in the availability of online gig platforms that arises from the rollout of platforms across counties over time. Second, I introduce within-area variation that permits me to split individuals into two groups: those who plausibly would even consider gig work, and those unlikely to take up gig work.

These two sources of variation allow me to identify the group of individuals who would have taken up gig work had it been available to them at the time of unemployment, but happened to face an unemployment shock in a county prior to the entry of gig platforms. The following two subsections describe both of these sources of variations in significantly more detail.

4.1 Variation in Gig Availability

I leverage variation in the date at which any online gig platform first enters city to measure the availability of gig work in a given city in a given year, or on the intensive margin, incorporating the "intensity" of gig availability based on characteristics such as the number of firms that are present in a city or how long gig platforms have been present. Crucially, this methodology identifies the availability of any gig firm rather than relying on the rollout of one specific gig platform.[26] Suppose that gig platforms first entered San Francisco in 2010, New York in 2011, and Los Angeles in 2012, then the thought experiment would be to compare an individual living in San Francisco after 2010 to a similar individual in San Francisco before 2010 as well as to individuals in New York and Los Angeles where platforms had not yet entered.[27] This closely relates to and builds upon several papers that have exploited variation driven by the launch of specific gig platforms, most commonly Uber, across cities(Brazil and Kirk, 2016; Dills and Mulholland, 2017; Berger et al., 2018; Hall et al., 2018; Koustas, 2018; Buchak, 2019). [28] A simple difference-in-difference exploiting the rollout variation assumes that the timing of gig firms' entry into a city is orthogonal to worker

[26]Gig availability relies on individuals working for any of the 50 or so large online platforms from publicly available lists, as mentioned in Section 2.2.
[27]This example is for illustrative purposes only.
[28]Mishel (2018) estimates that Uber makes up approximately two-thirds of the gig economy.

labor supply decisions.[29]

Figure 2 illustrates the geographical variation in gig availability and prevalence across counties in 2013 and 2016.[30] Each map of the US shows geographical variation by county in the percent of the working age population, those 15-64, with any earnings from gig work. Darker red shaded areas indicate a larger percentage of the county working age population have any earnings from gig work, while lighter beige colors indicate a smaller percentage. Substantial variation in this measure exists across counties over time. For example in 2013, in the counties surrounding the Los Angeles area less than 0.14% of working age individuals had any amount of gig work, whereas in 2016 counties surrounding most major US cities had up to 8.84% of the working age population with any gig work.

There are two important takeaways from the exhibited variation in the prevalence of gig work. First, over time more counties have any amount of gig availability as the various platforms rollout to new geographic markets. Second, the prevalence of gig work continues to increase within an area following the entry. This is driven by a myriad of factors that include the dissemination of information regarding a platform's presence that occurs naturally over time, increased demand for the services offered by a platform as more consumers become familiar with them, and the entry of additional platforms as not all necessarily enter a market in the same year.

Approximately 57% of the analysis sample faces an unemployment environment in which gig platforms were available to them in the year and county in which they received UI. Figure 3 shows the distribution of the selected UI events across years among those who had gig platforms available to them at the time of the unemployment shock in the solid gray line with shaded bars, and the distribution among those who did not have gig platforms available in the dashed black line with no shading. Not surprisingly, those without gig platforms available are concentrated slightly more towards the earlier years. As platforms roll out over time, only more individuals will have them as an option. In Table 2, I show balance on key observable characteristics prior to job loss for individuals with and without gig availability at UI receipt.

I define a measure 'Gig Intensity' that captures the magnitude of gig availability rather than a simple indicator for gig work being available as an option. In this measure, I want to capture any exogenous variation driven by overall trends in how the popularity and availability of these platforms grow after entering, on average, and exclude variation in the speed of growth arising from better or worse labor-market outcomes or prospects for workers in that area. Figure A7 plots the percentage of the working age population in a county-by-year relative to when gig platforms were first introduced in that county. A linear approximation appears to roughly fit the average

[29]Reiterating Footnote 3, the year of entry of gig platforms in a county is largely predicted by population. A simple regression of the year of gig entry on 2014 county population, as a cubic to pick up the curvature of the relationship, has an R squared value of 0.75.

[30]Appendix Figure A3 presents the same map year by year.

growth in gig prevalence following the entry of platforms into a county.

I consider the "treatment" of gig availability to occur at the time of UI receipt. Thus, as a function of the county c in which individual i lives in at the time of UI receipt t_i^0, I define Gig Intensity as:

$$\text{Gig Intensity}_i = \frac{(\text{\# Years Gig Available})_{c(i,t_i^0),t_i^0}}{\max_i(\text{\# Years Gig Available})_{c(i,t_i^0),t_i^0}} = \frac{1}{9}(\text{\# Years Gig Available})_{c(i,t_i^0),t_i^0}$$

I rescale this measure to be between 0 and 1 by dividing by 9, the max number of years gig platforms had been available in the county and year of UI receipt over all individuals. A value of 1 can be interpreted as becoming unemployed in an environment with the most gig availability relative to a value of 0 which indicates no gig availability. Among those individuals with any gig platforms, the median gig intensity value is $\frac{1}{3}$.

Appendix Figure A6 provides an example of how the gig intensity value varies across areas and years. Individuals receiving UI in years prior to gig platform entry will have a value of 0. For example, individuals in County C in Appendix Figure A6 who experience their job loss in the years 2008-2010 would have a gig intensity value of 0. Gig platforms enter County C in 2012, those receiving UI in 2012 would therefore have a value of $\frac{1}{9}$, 2013 would have a value of $\frac{2}{9}$, and so on.

4.2 Propensity for Gig Work

Since this time period covers the Great Recession as well as the post recession recovery, and the timing of entry of firms is correlated with population, it's plausible that labor-market outcomes in larger cities were recovering at different rates compared to smaller cities. Thus, a simple difference-in-differences would confound these two effects. Therefore, I employ a third difference that allows me to incorporate a within-area variation to pick up on local labor market changes.

I utilize pre-UI characteristics to predict an individual's propensity for gig work. Among treated individuals, the subset of individuals that had gig platforms available at UI receipt, I observe who takes up gig work and who does not. Thus, I estimate a probit regression of gig take up on pre-UI characteristics such as income, wages, EITC claiming, and demographic characteristics. With the probit estimates I predict a gig propensity for each individual, including those who did not have access to gig platforms. I split the sample into high-gig-propensity and low-gig-propensity, trying to capture all the potential gig workers in the high-gig-propensity group and everyone else in the low-gig-propensity group.

More specifically, I estimate a probit function where I look at gig take-up post UI as a function of the following pre-UI characteristics. First, I use demographic characteristics in the year prior to unemployment insurance claiming (i.e. at event time 0). These include a polynomial of an individual's age and their gender. I also utilize the zip code in which he or she lived in that year. Second, I use economic outcomes for the three years leading up to the claiming of UI. This incorporates a polynomial of wages, income, whether or not an individual had a wage job, any income from a sole proprietorship, and the share of the household earnings that the individual contributes, for those filing jointly. Third, I include filing status, marital status and number of claimed children living in the household.[31] Finally, I utilize information about the payer EIN in the year prior to UI receipt, as this provides additional, otherwise observable, information about the worker's characteristics and the likelihood of taking up gig work after losing their job at this firm.[32] Though I cannot identify an individual's exact occupation, I use 3-digit NAICS codes associated with the firm's EIN capturing information about the subsector in which that worker used to work.

I split the sample into three groups: high-gig-propensity, the top 1% of the sample in predicted gig probability; low-gig-propensity, the next 49% of the sample; and those excluded, the bottom 50% of the sample. By dividing the sample, I hope to capture all of the potential gig workers in the high-gig-propensity group. The low-gig-propensity group will also help to provide additional within-area variation for identification, as I describe in section 4.3. Additionally, I exclude the bottom 50% in predicted gig probability from the low-gig-propensity individuals to maintain a group of individuals that are more comparable to the high-gig-propensity individuals. I present the distribution of gig propensity scores separately by whether or not gig platforms were available in the county and year when an individual received UI in Appendix Figure A9a. Appendix Figure A9b shows the distribution of predicted gig propensities among the low group that I retain.

Summary Statistics on High and Low-gig-propensity Individuals

Table 3 presents summary statistics separately for high-gig-propensity and low-gig-propensity individuals. Relative to the low-gig-propensity sample of UI recipients, high-gig-propensity individuals are slightly more likely to be female (32% versus 30% female), and less likely to be married (28% versus 29%) or have children (37% vs 40%). On average, high-gig-propensity individuals have a lower household AGI, \$40,565 (vs \$46,130), and individual income, \$27,713 (vs \$32,025). They're also more likely to have held a gig work position in the pre-UI years, 0.16% vs 0.01%; though both groups have very low baseline values in this regard.

Figure A8 highlights additional variation in individuals' pre-UI characteristics and how they relate to the predicted gig propensity measure. For each, I plot the average predicted gig propensity by binned values for a few of the key predictive variables. Figure A8a demonstrates that younger

[31] These measures are conditional on filing, so for non-filers I code these individuals as single and without children, as done in Yagan (2019).

[32] For individuals with multiple W-2s, I use the payer EIN from the W-2 with the largest amount of wages.

individuals are more likely to work in the gig economy. This measure peaks around age 25 and, though not illustrated here, those below 25 have slightly lower propensities on average. Figure A8b and Figure A8c show that those with lower incomes and wages two years prior to UI receipt are more likely to participate in gig work. Figure A8d shows that individuals whose wages make up a larger share of the household's total wages are more likely to take up gig work, suggesting that these individuals are more likely to be the primary earner for the household.

4.3 Estimation Approach

I estimate a difference-in-difference-in-differences (DDD) specification that leverages variation in the availability of gig platforms at UI receipt and in individuals predicted propensity for gig work, as in Gruber (1994). Relative to a standard difference-in-differences, this strategy incorporates additional within-area treatment information. Since the availability of gig platforms should differentially affect the high-gig-propensity individuals compared to low-gig-propensity individuals, this additional interaction will help control for any other overall changes that coincide with treatment that affect the outcomes of all individuals, both high and low-gig-propensity. To the extent that there are other changes that affect all individuals unemployed in an environment with gig availability relative to no gig availability that are unrelated to the presence of gig platforms, incorporating low-gig-propensity individuals should account for these changes.

Formally, my estimating equation quantifying work in the gig economy is as follows:

$$Gig_{ict} = \alpha_i + \beta_1 P_{it} + \beta_2 (P_{it} * H_i) + \beta_3 (P_{it} * G_i) + \beta_4 (P_{it} * G_i * H_i) + \lambda_{ct} + \eta_{a(i)} + \Gamma X_{it} + \varepsilon_{ict} \quad (1)$$

P_{it} denotes that year t is post UI receipt for individual i, this includes the year of UI receipt. H_i is an indicator variable that an individual has a high predicted gig propensity. Denote E_i as the first year of UI receipt for individual i. Then G_i measures the intensity of gig availability that individual i faces at event time 0, $t = E_i$ in the county in which they live, $c_{i,t=E_i}$. I include individual fixed effects, county-by-year fixed effects (λ_{ct}), and single year-of-age fixed effects ($\eta_{a(i)}$).

With individual fixed effects, the effects are identified based off within-individual deviations from their mean outcome value. County-by-year fixed effects allow me to control for local labor market shocks that affect all individuals. My identification is driven by variation across individuals who do versus do not have gig platforms available to them, accounting for any existing differences across these counties and years as identified by differences across these groups among low-gig-propensity individuals. The key identifying assumption is that changes in the difference between high and low-gig-propensity individuals are not correlated with the intensity of gig availability.

The coefficient of interest is β_4. Since I have rescaled the gig intensity measure to be between 0 and 1, a value of 1 indicates becoming unemployed in an environment where gig platforms had been available the longest amount of time, among all individuals in my sample. Thus, the interpretation of the coefficient is the effect for a high-gig-propensity individual who became unemployed in an environment where gig platforms had been available for the maximum time relative to not being available at all, netting out any differences occurring overall captured by the low-gig-propensity group. The effect is estimated linearly in the treatment measure of gig availability so scaling the coefficient provides the effect size for a given treatment level. So, to get the effect of first receiving UI in an environment that had 50% of the maximum gig availability, a county and time combination where gig platforms had been available for half the number of years compared to the longest available, then you would multiply the coefficient by one half.

To estimate the effect of working in the gig economy following job loss on labor-market outcomes, I estimate an analogous set of reduced-form regressions with labor-market outcomes, Y_{ict}, as the dependent variable.

$$Y_{ict} = \alpha_i + \beta_1 P_{it} + \beta_2 (P_{it} * H_i) + \beta_3 (P_{it} * G_i) + \beta_4 (P_{it} * G_i * H_i) + \lambda_{ct} + \eta_{a(i)} + \Gamma X_{it} + \varepsilon_{ict} \tag{2}$$

Equation 2 estimates reduced-form estimates and identifies the causal effect of gig availability on unemployment outcomes. Scaling by the first stage take-up of gig work in Equation 1 would identify a “treatment on the treated” effect, or the effect of taking up gig work on unemployment outcomes in this context. This requires stronger assumptions: exclusion of the instrument and monotonicity (Angrist and Imbens, 1994). Taken together, these assumptions imply that the estimated changes among the high-gig-propensity individuals in earnings, labor force participation, and schooling, are only due to changes in the those who took up gig work.

5 Effects on Labor Supply and Earnings

I first present the results graphically with the coefficient of interest β_4 from Equation 2 split into year by year coefficients rather than just post. Equation 3 is exactly analogous to Equation 2 above, but a dynamic version. Event time, in years relative to UI receipt, is denoted by k. In each figure, I exclude the year two years prior to UI receipt, and so the coefficient estimates are relative to event time -2. Given the structure of the tax data, since I observe unemployment compensation at $k = 0$ it is possible that job loss occurred in year prior $k = -1$. Thus, to be conservative, I choose $k = -2$ to be the excluded year.

$$\begin{aligned} Y_{ict} = & \alpha_i + \sum_{k \neq 2} \theta_{1,k} \left(T_{it}^k \right) + \sum_{k \neq 2} \theta_{2,k} \left(T_{it}^k * H_i \right) + \sum_{k \neq 2} \theta_{3,k} \left(T_{it}^k * G_i \right) \\ & + \sum_{k \neq 2} \theta_{4,k} \left(T_{it}^k * G_i * H_i \right) + \lambda_{ct} + \eta_{a(i)} + \Gamma X_{it} + \varepsilon_{ict} \end{aligned} \tag{3}$$

$T_{it}^k = \mathbb{1}\{t = E_i + k\}$ represents a dummy indicating event time relative to the first year of UI receipt for individual i, E_i. The coefficients of interest in this specification are $\theta_{4,k}$.

5.1 Prime-Age Workers

Gig Employment and Earnings

First, I examine extensive margin measures of gig work to quantify to what extent individuals start working in the gig economy after losing their job. Figure 4a shows an increase of 10.16 percentage points, among high-gig-propensity individuals, in the year of UI receipt relative to two years prior for those with the most gig availability relative to no gig availability, netting out any changes occurring simultaneously among the low-gig-propensity individuals. Among low-gig-propensity individuals, there is no observed increase in gig work following UI receipt and for all individuals there is a base of roughly zero gig work in the pre-UI period.

In the year following UI receipt, this extensive margin increase is twice as large, a 19.63 percentage points increase relative to two years prior to UI. This is not surprising if we think individuals are waiting until they exhaust UI benefits before entering, then we would expect a distribution across months in when individuals exhaust UI benefits. In expectation, only about half of individuals would actually exhaust UI benefits in the same tax year as I first observe them receiving unemployment compensation, given a typical state's UI duration of 26 weeks and assuming UI recipients are randomly distributed throughout the year. As I only observe the year in which an individual receives unemployment compensation and not the month, I cannot differentiate between those starting UI benefits in February versus November.

The next important result from Figure 4a is that gig work increases among high-gig-propensity individuals following unemployment and then does not decline even four years after UI receipt. If individuals were using this only for a short period while searching for another job, then we would expect to see an increase in gig work but then a subsequent decrease when they switched to another job. However, we can immediately see that individuals enter into these positions and then stay in them.

In Figure 4b, I present the corresponding results with an intensive margin measure of gig work —gig earnings (in 2017 dollars).[33] The 10.16 percentage points increase in gig work corresponds to a roughly \$588 increase in gig earnings in the year of UI receipt. This implies that each individual working in the gig economy in the year of UI receipt is earning on average \$5,800 in that year. The first year following UI receipt, high-gig-propensity individuals with the maximum gig availability relative to no gig availability experience an increase in gig earnings of \$1,851, implying annual average gig earnings of roughly \$9,400. Implied average annual gig earnings for those with

[33] Dollars are adjusted using CPI-U from BLS: https://www.bls.gov/cpi/home.htm.

gig work two to four years after UI receipt are roughly \$14,000. For perspective, this is roughly similar to full-time equivalent earnings at federal minimum wage.[34]

As one of my key objectives in this paper is to disentangle short and long-run labor supply effects and motivated by the dynamic nature of the effects that I present, I separately estimate regressions for short- and long-run effects rather than pooling all post years, in Tables 4 and 5, respectively. In all regressions, I exclude one year prior to UI receipt since it is possible that job loss occurs in this period and therefore this may be a pre-unemployment period for some individuals and post-unemployment for others. In all regressions event years, $k \in [-5,-2]$ are considered pre-unemployment years. Short-run estimates present the immediate effect in the year of UI receipt ($k = 0$) as the post period of interest, while the long-run estimates consider $k \in [2,4]$ as the post period of interest. Pooled estimates include the entire post period $k \in [0,4]$.

In Table 4, I show that in the year of UI receipt gig work increases on the extensive margin by 10.51 percentage points and \$620.3 in gig earnings, for high-gig-propensity individuals relative to those without gig platforms available. As seen in Table 5, by two to four years after UI receipt the increase in gig work is 19.82 percentage points and \$2,831 in gig earnings. For completeness, I also present coefficients where I pool the short and long-run effects for all outcomes in Appendix Table A1.

Individual and Household Income

Given the increase in gig work, to what extent does this recover lost income with job loss? Figure 5 highlights the dynamic effects of gig availability at unemployment on individual income. First, there is a clear short-term smoothing effect. Column 3 of Table 4 shows that in the short run the income of high-gig-propensity individuals with the maximum gig availability when they lost their job, relative to that of individuals with no gig platforms available, dropped by \$3,118 less. As illustrated in Figure 5, this advantage fades away rapidly. By the year after UI receipt, those with and without gig availability at UI receipt have comparable and statistically indistinguishable changes in income.

Two to four years after UI receipt, the income of high-gig-propensity individuals who had gig platforms available at UI receipt lags behind comparable individuals who did not have gig platforms available. In Column 3 of Table 5, I present the coefficient estimate where I pool all three long-run post years. The coefficient -\$2,478 indicates that high-gig-propensity individuals with the maximum gig availability at the time of UI receipt is \$2,478 lower two to four years following UI receipt than comparable individuals who did not have any gig availability.

Appendix Figure A10 exhibits an analogous pattern for household income. Column 4 of Table 5 suggests a larger decrease of about \$4,847 when accounting for household income rather than

[34] \$15,000 is roughly 2,000 hours at the federal minimum wage, \$7.25. (https://www.dol.gov/whd/minimumwage.htm)

just individual income. Point estimates then drop below zero from one year post UI onwards. Together these results suggest that, among high-gig-propensity individuals, those with gig platforms available when they lose their job are better able to smooth income in the year of UI receipt. However, two to four years later, their income recovery starts to lag behind. The natural question is what drives this reversal?

Wage Employment and Earnings

Reversal in income recovery is explained by lower wages earnings, Figure 6a. This is largely a function of the extensive margin, holding a traditional wage job, as shown in Figure 6b. Examining the long-run outcomes, Column 5 of Table 5 indicates that annual wage earnings of high-gig-propensity individuals who had the maximum gig availability when they lost their job drop by $3,951 more than those with no gig platforms available when they lost their job. On the extensive margin, Column 6 indicates a 4.5 percentage points larger decrease in the probability of holding a traditional wage job. This is in contrast to the short-run, the year of UI receipt, there is no differential decrease in holding a wage job or wages in Table 4 Columns 5 or 6.[35]

Recall in Figure 4a that individuals entered into gig work and stayed in these positions even a few years later. This does not necessarily preclude the possibility of also holding a traditional wage job given the flexibility of gig work. However, these individuals are likely working close to full-time. Though I cannot directly observe hours, using estimates from the literature on typical hourly wages for Uber drivers —$9.21 (Mishel, 2018) —suggests that these individuals were likely working close to full-time given that on average they were earning roughly $14,000 annually. On the one hand, these individuals might be working so intensively on gig platforms because they have not received a job offer to re-enter a traditional wage position, but are searching. On the other hand, it is similarly possible that individuals are working so extensively that they do not have time to search for another job. Finally, it may be that these individuals enter these positions following job loss, learn they value the flexibility offered by gig work, and choose to stay accepting lower earnings because they value the flexibility.

5.2 Older Workers

Now I turn to older workers, individuals between the ages of 55 and 69 at the time of UI receipt. Compared to prime-age workers, older workers are particularly vulnerable in that they have a more difficult time of finding re-employment following job loss and thus typically behave differently following job loss. Furthermore, they may especially value the flexible nature of gig work as a

[35]Note there is a decrease in wages in Table 4 Column 4 that is about one-third of baseline wages in the post period for all individuals; however, the extensive margin coefficient is small given that many individuals still receive a W-2 in the year of UI receipt.

bridge to retirement (Ramnath et al., 2017).[36]

Following my empirical strategy for prime-age workers exactly, I estimate an analogous set of regressions and figures using Equations 1, 2, and 3 for the sample of older workers. I present summary statistics for this older age group in Table 6. Among this sub-population (55-69), approximately 80% are under age 65. The average individual is 56 years old (and the median individual is 55 years old). [37]

Gig Employment and Earnings

Compared to prime-age workers, older workers exhibit a similar increase in gig work following job loss, Figure 7a. Figure 7a indicates that among the high-gig-propensity individuals who became unemployed in a county and year with the highest gig availability relative to having no gig availability increased gig work by 15.76 and 31.39 percentage points in the year of and year following UI receipt, respectively. This corresponds to an increase of $1,248 and $4,430 in gig earnings, Figure 7b.

The extensive margin increase for high-gig-propensity older workers is almost twice as large in magnitude as observed for high-gig-propensity prime-age workers. Furthermore, above and beyond the larger extensive margin increase in gig work, the implied gig earnings for each gig worker on average are also higher. Table 7 and 8 indicate an increase in gig work (and gig earnings) of 16.23 percentage points ($1,233) and 33.09 percentage points ($6,423) in the short-run and long-run, respectively. These estimates imply that each gig worker is earning on average $7,600 in the short-run and $19,400 in the long-run, and are both approximately 30% larger than we saw for prime-age workers.

Individual and Household Income

Unlike among prime-age workers, older workers with gig availability do not exhibit the same reversal pattern in income relative to those without gig platforms at the time of job loss (see Appendix Figure A11). If anything, the point estimates in Appendix Table A2 suggest that individuals with the maximum gig availability maintain the relative increase of about $5,204 in individual income and $6,000 in household AGI, though the coefficients are not statistically significant. Again, these coefficients are for high-gig-propensity individuals who first receive UI in an environment with the maximum gig availability (as a function of county-by-time) relative to comparable individuals

[36]While Ramnath et al. (2017) find transitions into self-employment as a bridge job between career employment and retirement less common than expected, this may be due to the fixed costs of entering self-employment, which are higher than working on a gig platform. Additionally, they examine this in the context of overall workforce transitions where as I examine individuals facing an unexpected job loss and who are therefore likely not ready to retire.

[37]Note that these are averages in the years prior to UI receipt, while the sample is restricted to individuals 55-69 at the time of UI receipt, these individuals will be a few years younger in the years prior.

with no gig availability when they received UI.

Social Security Disability Insurance (SSDI)
Their counterparts, without gig availability, receive SSDI benefits and claim social security retirement benefits rather than returning to the traditional wage workforce, as do the prime-age workers. Figure 8 highlights a pronounced drop in the receipt of SSDI in the post-UI period. These coefficients indicate that high-gig-propensity individuals with gig availability receive SSDI benefits at lower rates than those without gig availability at UI receipt. More specifically, Table A2 shows this is a significant reduction of 5.9 percentage points in the receipt of SSDI benefits for those with the most gig availability relative to no gig availability. This suggests that these individuals are on the margin between working and not. Therefore, this has important fiscal implications.

Social Security Retirement
Additionally, the increase in gig participation and earnings through gig platforms postpones withdrawing social security benefits. Figure 9 is noisier and there is not an obvious and large drop in withdrawing Social Security retirement benefits. However, given the large confidence intervals due to a small sample, I cannot rule out effects that would be substantial. There is a 1.3 percentage points reduction in the short run and 4.4 percentage points reduction in the long run (two to four years after UI) in claiming Social Security retirement benefits among individuals with job loss with the most gig availability relative to no gig availability. The negative coefficients indicate that those with gig availability are less likely to withdraw social security benefits relative to those with no gig availability. This indicates that gig work is crowding out increases in claiming Social Security retirement benefits that follow UI receipt.

Since only a sub-group of older workers can actually respond on this margin, those ages 62-67, I zoom in on this group for power in Appendix Figure E1 and Appendix Table E1. Among these individuals, there is a 14 percentage points reduction in Social Security retirement benefits following UI receipt. This can be financially advantageous for two reasons. First, as shown in Shoven and Slavov (2014), delaying benefits is generally actuarially advantageous. Second, by working longer, they can only increase their future lifetime benefits by potentially increasing the value of the highest years in their earnings history or decreasing the number of years with no earnings that are taken into account when calculating an individual's benefit.

5.3 Robustness and Placebo Exercises

In this section, I address two potential concerns with my main identification strategy. First, I present two plots showing robustness around my definition of high and low-gig-propensity. At baseline, I define high-gig-propensity as the top 1% of the predicted propensity distribution, exclude the lowest 50% of the distribution, and define low-gig-propensity as the remaining middle 49%. In Appendix Figure A12, I examine two alternative definitions. First, I present results including all of the bottom 99% of the predicted propensity distribution in the low-gig-propensity group. Second, maintaining my baseline definition of low-gig-propensity, I instead alter the definition of high-gig-propensity to encompass a broader group of individuals, and include the top 3% rather than 1% of predicted gig propensities.

As seen in Appendix Figure A12a, incorporating the lowest 50% of predicted propensities in the low-gig-propensity group, if anything increases the point estimates slightly for gig work. On the other hand, broadening the definition of high-gig-propensity dampens the measured effect on gig work among the high-gig-propensity group. This is not surprising, as increasing the scope of the high-gig-propensity group means more individuals who are less likely to take up gig work are included. Appendix Figure A12b shows the corresponding estimates for individual income under each definition of high and low. Reassuringly, the patterns of individual income are similarly more muted for alternative high definitions with lower estimates for gig work. This provides additional support that the observed changes in income are driven from those taking up gig work. I have altered the definition of high to various other thresholds between 1%-5% and observe qualitatively similar patterns.

Second, since propensity for gig work closely relates to income and the order of platform entry is correlated with city size, another potential concern might be that higher and lower income individuals in larger versus smaller areas might have differential recovery in income following unemployment. To address this concern, I run a placebo test where I draw a new random sample of UI recipients from 2002-2005, prior to the availability of gig platforms. Using the same coefficients from the probit regression described in Section 4.2, I generate predicted gig propensities for this placebo sample and similarly split them into high and low-gig-propensity. To simulate gig availability, I subtract 9 years from the first year of gig availability by county in order to generate a placebo gig availability measure that maintains the relative ordering of the platform rollout. I then calculate the gig intensity measure as a function of these new placebo gig entry dates.

I estimate an analogous regression using Equation 3 for the key outcome variable for prime-age workers, individual income. As seen in Appendix Figure A13, there is no clear pattern of differential changes in income post unemployment. Additionally, there is no longer the inverse U-shape showing the reversal of relative income as seen in Figure 5. Thus, I find this reassuring that the results I find are not driven by differential trends post-unemployment across the different groups.

6 Discussion and Mechanisms

Given that a new choice is being introduced, in this case the gig economy, it is perhaps surprising that in the long run high-gig-propensity prime-age workers have lower earnings. A natural question is whether or not this is rational. The following are a few mechanisms that may account for these results. First, individuals may be learning that they value flexibility and are willing to take an earnings loss for the flexible amenity. Second, on the other extreme, this could be consistent with a behavioral story. An individual plans to use the gig economy in the short run to get back on their feet and search for a new job, however they procrastinate (e.g. O'Donoghue and Rabin (2001)) and the time they spend working on the gig platforms ultimately crowds out the search effort. Finally, potential employers might view the time spent working for online gig platforms as undesirable, or if not disclosed on one's resume it may look like a longer period of unemployment.[38]

This study can help distinguish which of these mechanisms may be at play. First, building on the literature that examines the value of flexibility as a job amenity, I use the regression estimates differentiating long-term differences in individual income as a way to infer individuals' value for flexibility. Precisely, individuals taking up gig work earn approximately 12,502 fewer dollars per year than their non-gig counterparts in the long-run, or 2-4 years after UI receipt.[39] On average, these individuals earn approximately $32,000 annual in individual income, implying that they are willing to forgo 39% of their earnings in exchange for flexibility.

This number is very high relative to findings in earlier literature; for instance, (Mas and Pallais, 2017) find estimates of an individual being willing to forfeit up to 20% of earnings, on average, in the most extreme case where an employer can set their schedule on short notice.[40] One consideration is that in prior studies, values of flexibility were considered under different contexts and might not necessarily reflect the same degree of flexibility and hence of valuation. This suggests that either individuals in this context are either on the extreme end of the distribution in their valuation for flexible work arrangement, or that there is a behavioral story at play.

Furthermore, we can consider what discount rate would an individual need to have in order to rationalize the pattern of earnings observed among gig workers, with higher short-term earnings and lower long-term earnings. These individuals would need to have a discount factor of at most $\delta = 0.86$ (or an implied interest rate of at least 0.16) to rationalize the choice between the present

[38] Adermon and Hensvik (2022) show that in Sweden listing a gig job on one's resume improves callback rates for individuals with Swedish sounding names and not Muslim sounding names.

[39] Using the estimates from Table 5, 19.82% of high-propensity individuals taking up gig work and earn approximately 2,478 fewer dollars than their non-gig counterparts (-2,478/.1982).

[40] Note, that value of flexible work arrangements are also considered in the context of the gig economy, specifically ride share, in Chen et al. (2019) and find high valuation for flexibility, but in comparison with a non-flexible job in a similar high wage fluctuation scenario, which differs from the considerations here.

discounted value of taking up gig work opposed to not.[41] Prior studies suggest this is a low discount factor (Frederick et al., 2002). [42]

Estimates may be consistent with a $\beta - \delta$ type model and time-inconsistent preferences (Strotz, 1956; Ainslie, 1991; Laibson, 1997; O'Donoghue and Rabin, 1999, 2001; Frederick et al., 2002; Augenblick et al., 2015). Under this model, individuals have a present-bias and may continue to hold off searching until the next day, and choose to work their gig job today. To the extent this is occuring suggests the need for a policy intervention to help younger workers exit gig work and return to traditional work after a short-run recovery. Together these estimates suggest that either these individuals are have extreme values for flexibility, and are outliers in their preferences, or individuals are perhaps procrastinating and not fully optimizing. Future work can help shed light on if either or both of these types of individuals are present.

7 Conclusion

In summary, I document an increase in gig work after job loss (UI receipt). DDD estimates indicate an increase of 18 percentage points in annual gig-work participation post-UI receipt among the high-gig-propensity individuals. Correspondingly, the high-gig-propensity individuals with gig platforms available experience a smaller drop in individual and household income in the year of UI receipt relative to comparable individuals without gig platform availability. However, this income smoothing advantage is short-lived, and by two years after UI receipt individual and household income actually start lagging behind their counterparts without gig availability. This is explained by a reduction in traditional wage employment and wage earnings.

Crucially, the implications depend on what counterfactual behavior is being crowded out. For prime-age workers (25-54), it appears to crowd out wage jobs that provide individuals with an upward earnings trajectory, offer important employer-sponsored benefits, and are covered by workplace protections. While for older workers (55-69), the new option of gig work prolongs labor force participation. In doing so, this reduces receipt of SSDI benefits and postpones claiming of Social Security retirement benefits. Thus, the effects appear positive in terms of the long-run implications among older workers.

When examining potential mechanisms at play for the prime-age workers, estimates suggest one of two things. Either individuals have extreme values of flexibility, as compared to values in prior studies that examine willingness to pay for flexibility, as well as low discount factors. Alternatively, individuals may be subject to procrastination and obsolescence, and not fully optimizing

[41] This compares the present discounted value of high-propensity individuals with gig work available to those without gig work in years 0-4. A discount factor $\delta \leq 0.86$ is necessary for discounted earnings to be higher for taking up gig work.

[42] There are experimental studies that have found low discount factors; though this is a non-experimental study.

their search behavior. To the extent that this is occurring, suggests the need for a policy intervention to help younger workers search for full employment while in the gig economy. While the gig positions help individuals cushion job loss in the short-run by providing valuable insurance, individuals are not shifting back to traditional jobs. Future research can help examine the extent to which extreme preferences versus behavioral biases are at work, and it is possible that both types of individuals are present.

Beyond the mechanisms at play, the shift towards gig employment is particularly important because the US systems of benefit coverage and tax administration depend on the employer-employee relationship. Most Americans receive health insurance coverage, retirement plan coverage, and related benefits from their employer, in large part because of tax preferences that favor employer-provided coverage. While health insurance coverage is improving for these groups with policies such as the Affordable Care Act (ACA), gaps in coverage for health and, especially, retirement benefits remain for this growing group of self-employed (Jackson et al., 2017). Hence, changes in the employer-employee relationship and shifts toward the non-employee workforce have important consequences for benefit coverage, tax administration, and other labor and tax policy-related issues. Thus, the implications are more complex than simply measuring changes in income.

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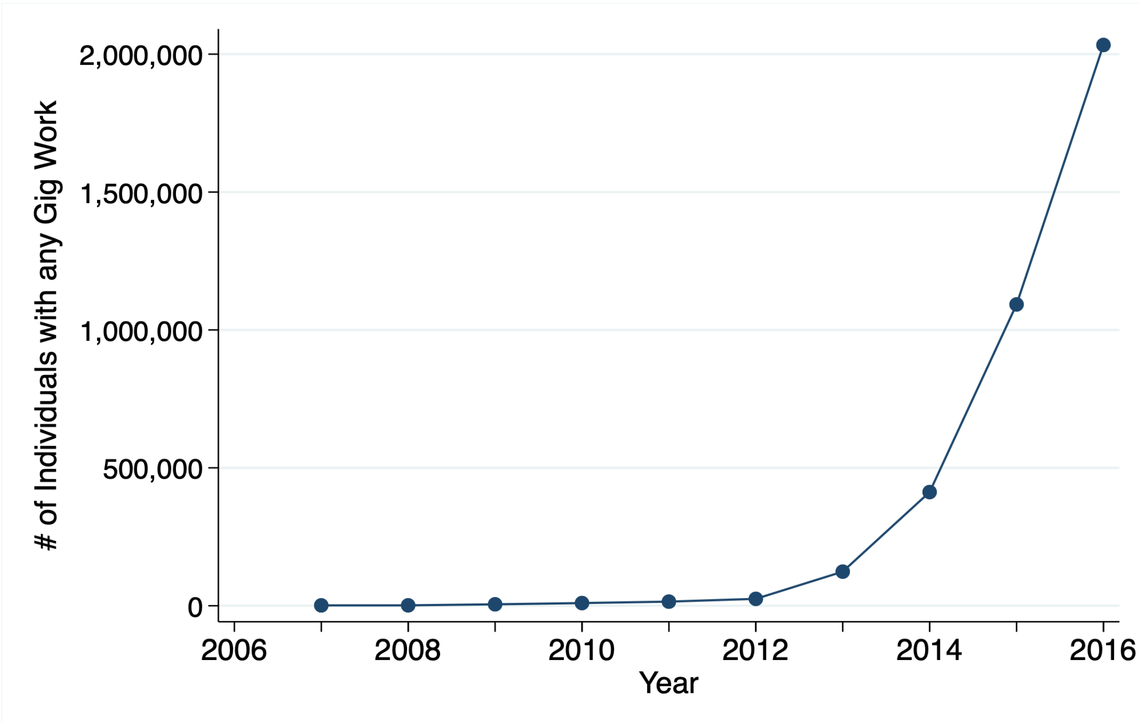
Figures and Tables

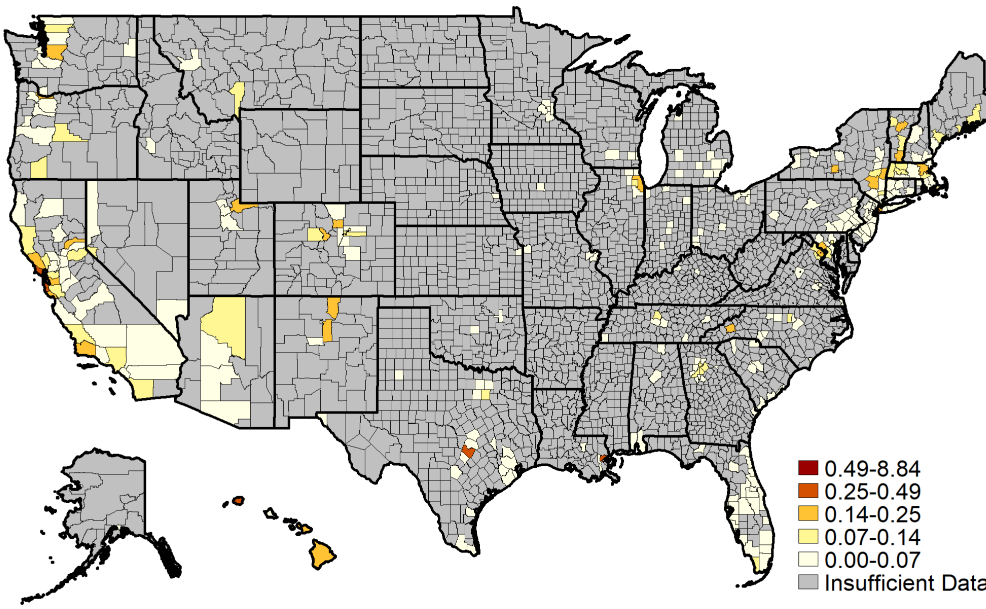
Figure 1: Number of Gig Workers by Year



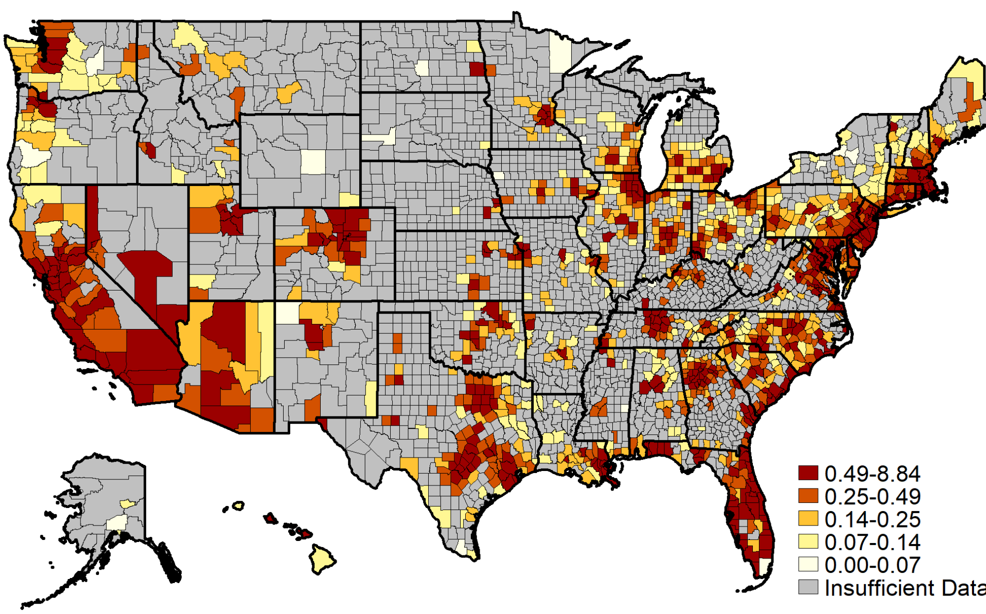
Notes: This figure presents the yearly number of individuals with any gig work as identified using the universe of federal individual income tax returns for the US. This includes counts of the universe of individuals who received Form 1099-MISC or Form 1099-K from a gig platform, as described in Section 2.2, or filed Schedule C denoting income from one of these platforms.

Figure 2: Percent of a County's Working Age Population (15-64) Partaking in Gig Work

(a) Variation in 2013

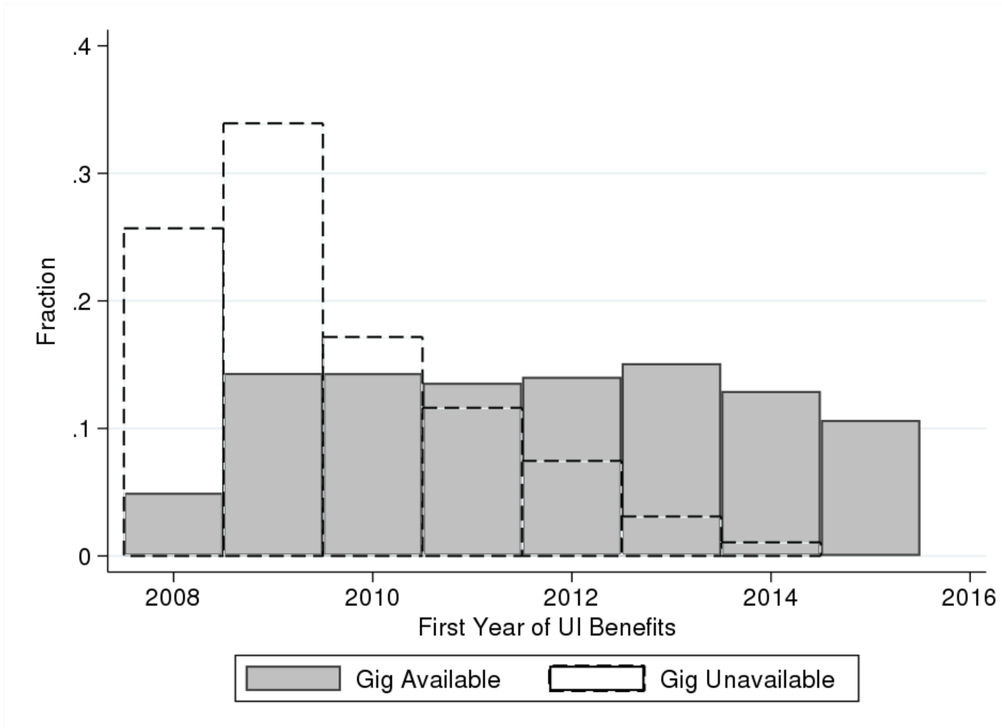


(b) Variation in 2016



Notes: Figure 2a and 2b illustrate the geographic variation in gig platform availability at a given point in time across counties. Second, they illustrate variation within a county over time in the prevalence of gig work, as measured in the percent of the counties working age population with any amount of gig earnings in that year. "Insufficient Data" means that a cell has fewer than 30 observations with any gig work and are suppressed; predominantly, these consist of zeros rather then suppressed data points.

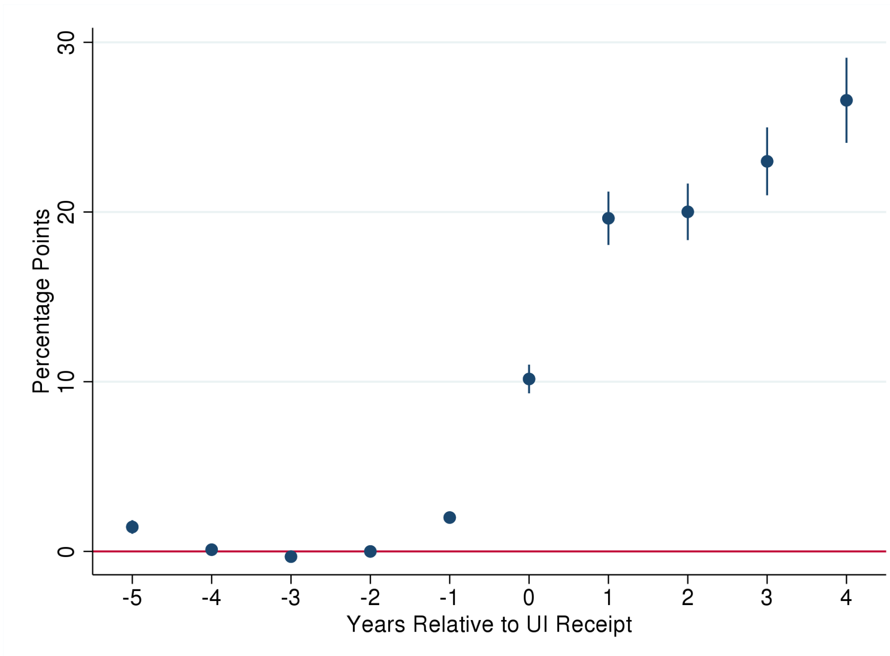
Figure 3: Distribution of Gig Availability Among UI Recipients Across Years



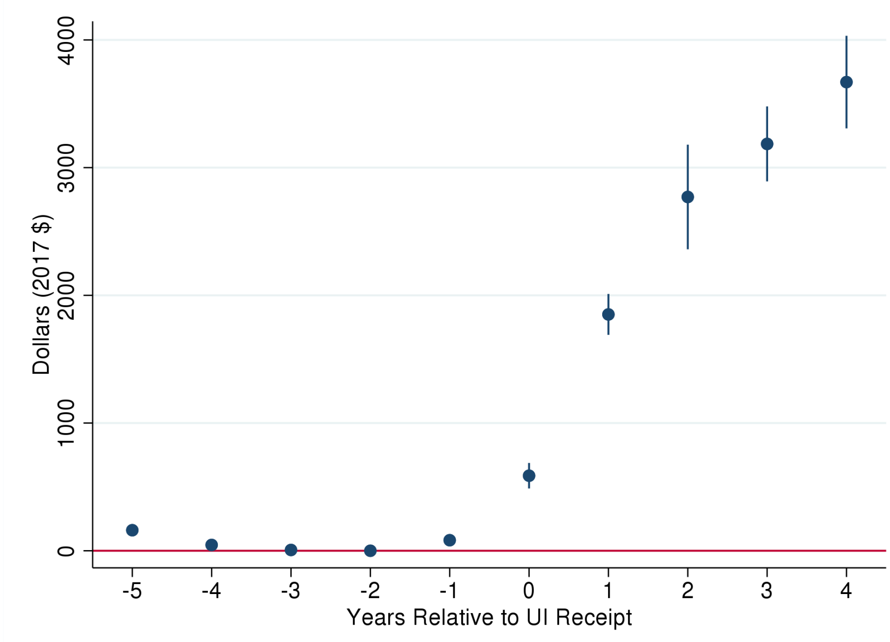
Notes: 'Gig Available' denotes the subset of individuals who had gig platforms available in the county and year in which they first receive UI benefits and are shown above with a solid blue line with shaded bars. 'Gig Unavailable' denotes the subset of individuals who did not have gig platforms available to them in the county and year in which they first receive UI and are shown above with a black dashed line and un-shaded bars. The distribution among each group sums to 1, and 57% of the sample had gig platforms available at UI receipt.

Figure 4: Yearly Coefficients for Gig Work
(Prime-Age Workers)

(a) Gig Work (x 100)

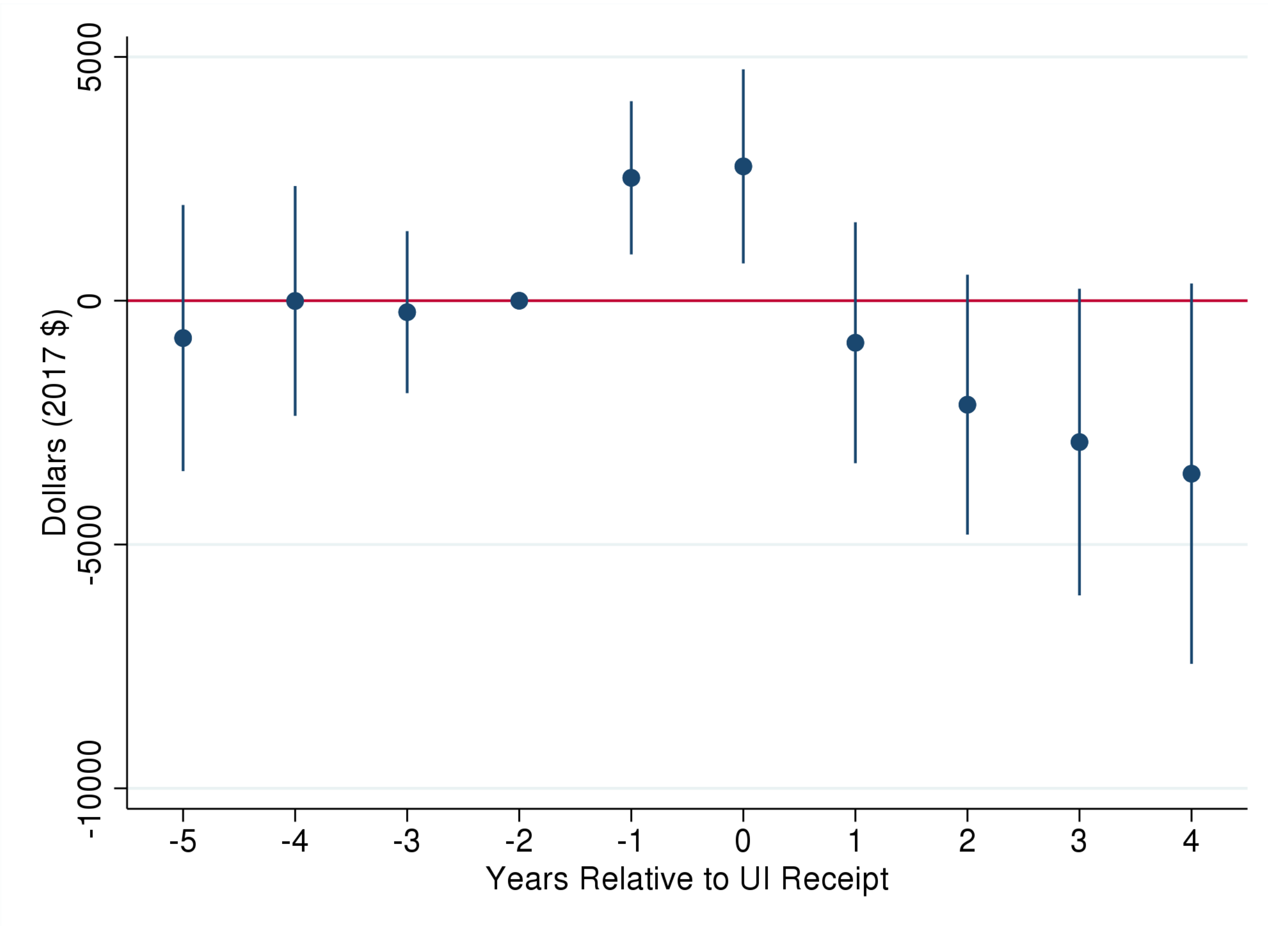


(b) Gig Earnings (2017)



Notes: Dependent variable in the top panel is an indicator for participating in gig work, expressed in percentage points (taking the values 0 or 100). Dependent variable in the bottom panel is Gig Earnings (in 2017 $). Coefficient estimates for $T_{it}^k * G_i * H_i$ are plotted for each year in event time relative to event time k=-2. These estimates are interpreted as the effect of having the most gig availability at UI receipt compared to no gig availability among high-gig-propensity individuals, differencing out any changes that occur among the low-gig-propensity individuals, and each yearly coefficient is relative to two years prior to UI receipt. Sample balanced on event time $k \in [-3, 2]$. Regression includes individual FEs, county-by-year FEs, and age FEs. Data drawn around UI recipients first UI event in the period 2008-2015 and includes observations from 2005-2017. Robust standard errors clustered by individual.

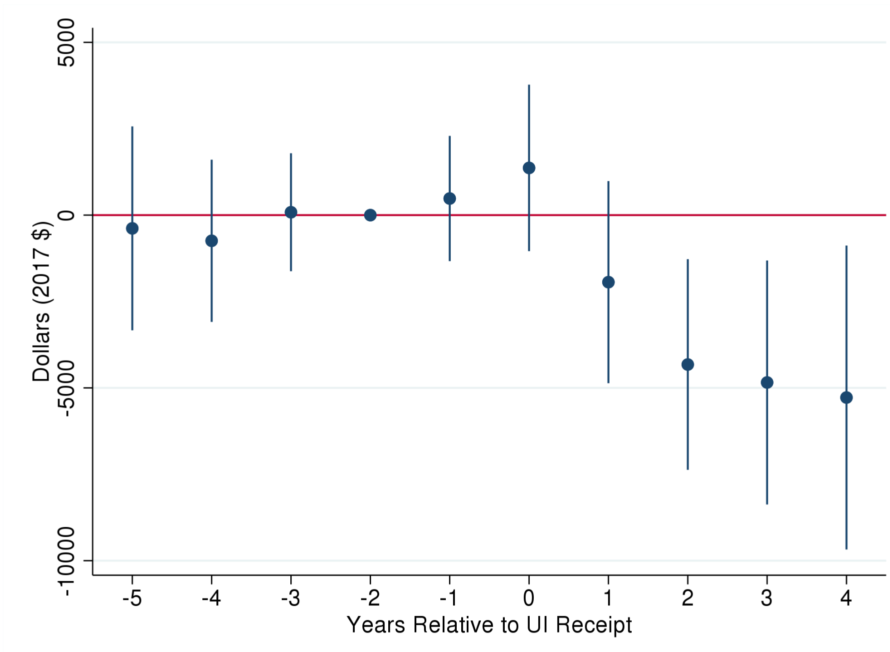
Figure 5: Yearly Coefficients for Individual Income
(Prime-Age Workers)



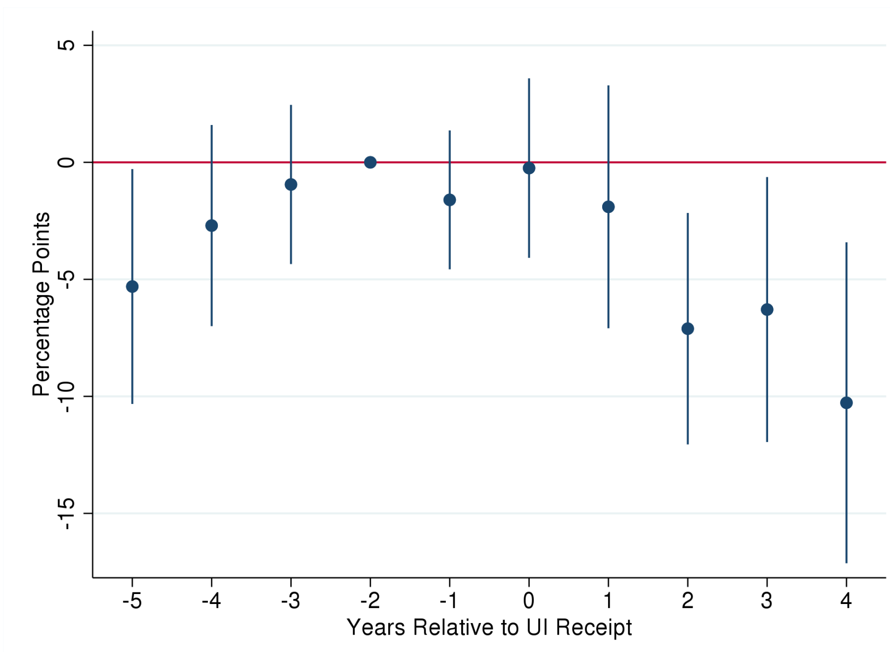
Notes: Dependent variable is individual income (2017 $), and the top and bottom 1% of values are winsorized. Coefficient estimates for $T_{it}^{k} * G_i * H_i$ are plotted for each year in event time relative to event time k=-2. These estimates are interpreted as the effect of having the most gig availability at UI receipt compared to no gig availability among high-gig-propensity individuals, differencing out any changes that occur among the low-gig-propensity individuals, and each yearly coefficient is relative to two years prior to UI receipt. Sample balanced on event time $k \in [-3, 2]$. Regression includes individual FEs, county-by-year FEs, and age FEs. Data drawn around UI recipients first UI event in the period 2008-2015 and includes observations from 2005-2017. Robust standard errors clustered by individual.

Figure 6: Yearly Coefficients for Wage Employment
(Prime-Age Workers)

(a) Wage Earnings (2017 $)



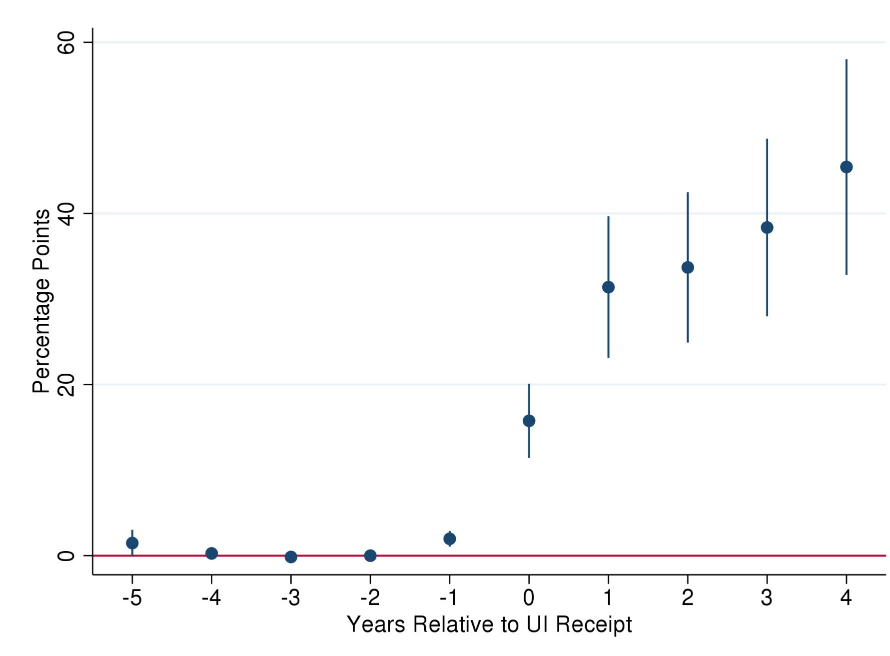
(b) Wage Job (x 100)



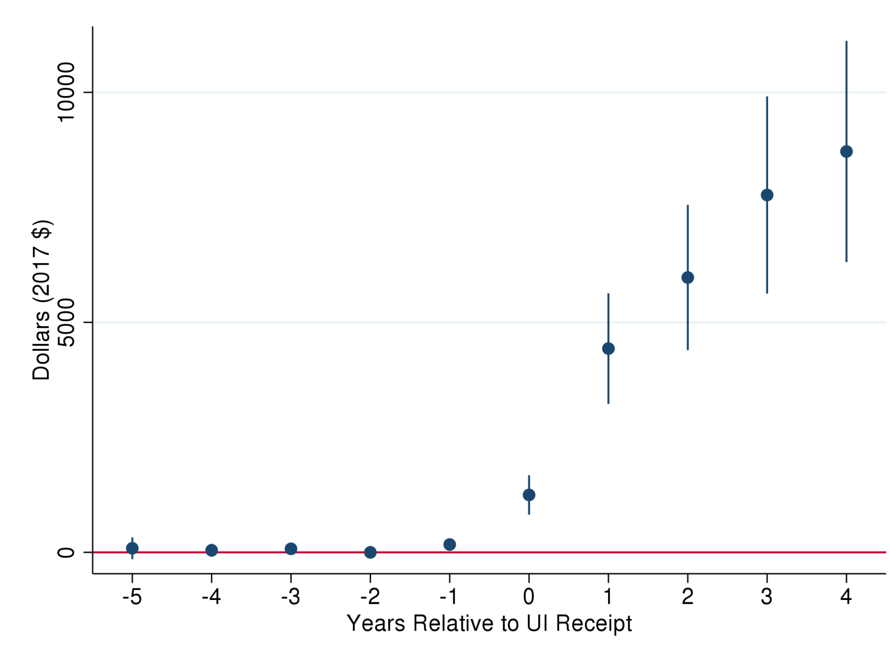
Notes: Dependent variable in the top panel is wage earnings (2017 $), and the top 1% of values are winsorized. Dependent variable in the bottom panel is an indicator for wage job (in percentage points 0 or 100). Coefficient estimates for $T_{it}^{k} * G_i * H_i$ are plotted for each year in event time relative to event time k=-2. These estimates are interpreted as the effect of having the most gig availability at UI receipt compared to no gig availability among high-gig-propensity individuals, differencing out any changes that occur among the low-gig-propensity individuals, and each yearly coefficient is relative to two years prior to UI receipt. Sample balanced on event time $k \in [-3, 2]$. Regression includes individual FEs, county-by-year FEs, and age FEs. Data drawn around UI recipients first UI event in the period 2008-2015 and includes observations from 2005-2017. Robust standard errors clustered by individual.

Figure 7: Yearly Coefficients for Gig Work
(Older Workers)

(a) Gig Work (x 100)

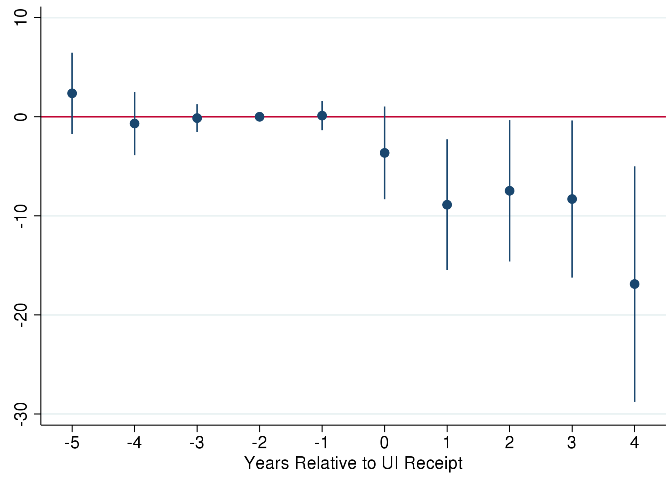


(b) Gig Earnings (2017)



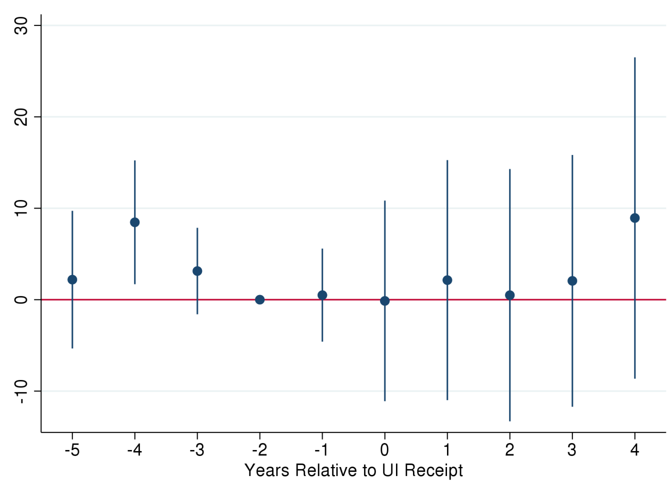
Notes: Dependent variable in the top panel is an indicator for participating in gig work, expressed in percentage points (taking the values 0 or 100). Dependent variable in the bottom panel is Gig Earnings (in 2017 $). Restricted to the older worker sample, ages 55-69 at the time of UI receipt. Coefficient estimates for $T_{it}^{k} * G_i * H_i$ are plotted for each year in event time relative to event time k=-2. These estimates are interpreted as the effect of having the most gig availability at UI receipt compared to no gig availability among high-gig-propensity individuals, differencing out any changes that occur among the low-gig-propensity individuals, and each yearly coefficient is relative to two years prior to UI receipt. Sample balanced on event time $k \in [-3, 2]$. Regression includes individual FEs, county-by-year FEs, and age FEs. Data drawn around UI recipients first UI event in the period 2008-2015 and includes observations from 2005-2017. Robust standard errors clustered by individual.

Figure 8: Yearly Coefficients for Social Security Disability Insurance
(Older Workers)



Notes: Dependent variable is an indicator having received SSDI benefits (in percentage points 0 or 100). Restricted to the older worker sample, ages 55-69 at the time of UI receipt. Coefficient estimates for $T_{it}^{k} * G_i * H_i$ are plotted for each year in event time relative to event time k=-2. These estimates are interpreted as the effect of having the most gig availability at UI receipt compared to no gig availability among high-gig-propensity individuals, differencing out any changes that occur among the low-gig-propensity individuals, and each yearly coefficient is relative to two years prior to UI receipt. Sample balanced on event time $k \in [-3, 2]$. Regression includes individual FEs, county-by-year FEs, and age FEs. Data drawn around UI recipients first UI event in the period 2008-2015 and includes observations from 2005-2017. Robust standard errors clustered by individual.

Figure 9: Yearly Coefficients for Social Security Retirement Benefits
(Older Workers)



Notes: Dependent variable is an indicator having claimed Social Security Retirement benefits (in percentage points 0 or 100). Restricted to the older worker sample, ages 55-69 at the time of UI receipt. Coefficient estimates for $T_{it}^{k} * G_i * H_i$ are plotted for each year in event time relative to event time k=-2. These estimates are interpreted as the effect of having the most gig availability at UI receipt compared to no gig availability among high-gig-propensity individuals, differencing out any changes that occur among the low-gig-propensity individuals, and each yearly coefficient is relative to two years prior to UI receipt. Sample balanced on event time $k \in [-3, 2]$. Regression includes individual FEs, county-by-year FEs, and age FEs. Data drawn around UI recipients first UI event in the period 2008-2015 and includes observations from 2005-2017. Robust standard errors clustered by individual.

Table 1: Pre-UI Summary Statistics

	Mean	Std Dev	P10	Median	P90
Female	0.30	0.46			
Age	33	33	23	31	45
Married	0.29	0.45			
Any Children	0.39	0.49			
Household Filed	0.91	0.29			
Household AGI (2017 $)	45,997	39,667	9,700	34,500	98,100
Individual Income (2017 $)	31,920	25,561	4,000	27,000	63,900
Wage Job	0.91	0.29			
Wages (2017 $)	33,204	29,286	400	27,900	70,200
Spouse's Wages (2017 $)	8,362	19,998	0	0	36,000
Schedule C Profit/Loss (2017 $)	475	3,908	0	0	0
Schedule C (HH)	0.15	0.36			
Gig Year	0.00	0.01			
Student	0.17	0.38			
Has SSDI	0.0040	0.0627			
Has SS Income	0.0012	0.0342			
Claimed EITC (HH)	0.28	0.45			

Notes: Summary statistics are for the three years prior to UI receipt. P10 and P90 represent the 10th and 90th percentile values of the corresponding variables. All P10, Median, and P90 values are rounded for confidentiality of taxpayer data. Married is taken from an individual's filing status. Any Children is an indicator for if a household claimed any dependents in that year. Household Filed denotes that an individual or their spouse filed an Individual Tax Return in that tax year (Form-1040). Household AGI is the adjusted gross income drawn directly from the Individual Tax Return. Individual Income additionally incorporates non-filing earnings by summing information returns (e.g. W-2s, 1099s, etc.) and divides AGI in half for married filing jointly individuals. Wage job is an indicator for receiving a W-2. Wages is the sum of wages across all W-2 forms received by an individual. Spouse's Wages is the sum of wages across all W-2 forms received by an individual; this value is 0 if a spouse has no wages or an individual does not have a spouse, and is missing for non-filers. Schedule C Profit/Loss denotes the amount of profit/loss claimed on Sch C. Schedule C (HH) is an indicator for either the individual or spouse having filed Schedule C for income earned through a sole-proprietorship. Gig Job is an indicator for having an earnings from gig work. Student is an indicator for having an eligible tuition payment at a post-secondary institution. Has SSDI is an indicator for receiving Social Security Disability Insurance (Form 1099-SSA). Has SS Income is an indicator for withdrawing Social Security Retirement Income (Form 1099-SSA). Claimed EITC (HH) is an indicator that a Household claimed the EITC in that tax year.

Table 2: Balance Table by Gig Availability

	(1) Gig Unavailable	(2) Gig Available	(1) - (2) P-Value
Age	33.97	34.78	(0.429)
Female	0.252	0.337	(0.510)
1 Year Prior to UI Receipt:			
Wages ('000 $)	38.02	39.24	(0.408)
Income ('000 $)	47.78	48.19	(0.203)
Married	0.346	0.286	(0.000)***
Student	0.136	0.136	(0.027)**
Wage Job	0.953	0.964	(0.521)
HH Wage Share	0.888	0.910	(0.010)**
Tax Filer	0.943	0.939	(0.756)
Claimed EITC (HH)	0.281	0.290	(0.767)
Filed Sch C (HH)	0.163	0.153	(0.331)
2 Years Prior to UI Receipt:			
Wages ('000 $)	35.90	36.30	(0.412)
Income ('000 $)	45.64	45.34	(0.294)
Married	0.339	0.279	(0.001)***
Student	0.150	0.158	(0.014)**
Wage Job	0.934	0.922	(0.453)
HH Wage Share	0.884	0.906	(0.049)**
Tax Filer	0.916	0.908	(0.100)
Claimed EITC (HH)	0.263	0.273	(0.251)
Filed Sch C (HH)	0.162	0.156	(0.291)
3 Years Prior to UI Receipt:			
Wages ('000 $)	33.16	33.58	(0.626)
Income ('000 $)	43.15	42.55	(0.361)
Married	0.327	0.265	(0.015)**
Student	0.162	0.178	(0.002)***
Wage Job	0.909	0.885	(0.364)
HH Wage Share	0.883	0.906	(0.156)
Tax Filer	0.890	0.879	(0.965)
Claimed EITC (HH)	0.248	0.255	(0.288)
Filed Sch C (HH)	0.163	0.155	(0.070)*
Observations	235,598	499,337	734,935
F-test of joint significance			1.8008

Notes: Columns 1 and 2 present mean values for individuals with UI receipt when gig platforms were and were not available, respectively. The third column shows the p-values for the difference in sample means controlling for year FEs and county FEs. Income is individual income as define in Table 1. Married is taken from an individual's filing status. Student is an indicator for having an eligible tuition payment at a post-secondary institution. Wage job is an indicator for receiving a W-2. HH Wage Share is an individual's wage earnings as a fraction of the sum of the individual's and spouse's wages. Tax Filer denotes that an individual or their spouse filed an Individual Tax Return in that tax year (Form-1040). Claimed EITC (HH) is an indicator that a Household claimed the EITC in that tax year. Filed Schedule C (HH) is an indicator for either the individual or spouse having filed Schedule C for income earned through a sole-proprietorship.

Table 3: Pre-UI Summary Statistics —by Gig Propensity
(Prime-Age Workers)

	High Gig Propensity					Low Gig Propensity				
	Mean	Std Dev	P10	Median	P90	Mean	Std Dev	P10	Median	P90
Female	0.32	0.47				0.30	0.46			
Age	33	8	23	31	45	33	8	23	31	45
Married	0.28	0.45				0.29	0.45			
Any Children	0.37	0.48				0.40	0.49			
Household Filed	0.90	0.30				0.91	0.29			
Household AGI (2017 $)	40,565	37,278	8,200	29,400	88,300	46,130	39,714	9,700	34,700	98,300
Individual Income (2017 $)	27,713	23,386	2,300	22,900	56,500	32,025	25,604	4,000	27,200	64,100
Wage Job	0.89	0.32				0.91	0.29			
Wages (2017 $)	27,459	25,287	0	22,500	59,200	33,347	29,364	400	28,000	70,500
Spouse's Wages (2017 $)	8,594	21,006	0	0	36,700	8,357	19,972	0	0	36,000
Schedule C Profit/Loss (2017 $)	600	4,324	0	0	1300	472	3,898	0	0	0
Schedule C (HH)	0.19	0.40				0.15	0.36			
Gig Year	0.00	0.04				0.00	0.01			
Student	0.19	0.39				0.17	0.38			
Has SSDI	0.0029	0.0533				0.0040	0.0629			
Has SS Income	0.0009	0.0298				0.0012	0.0343			
Claimed EITC (HH)	0.30	0.46				0.28	0.45			

Notes: Summary statistics are for the three years prior to UI receipt. P10 and P90 represent the 10th and 90th percentile values of the corresponding variables. All P10, Median, and P90 values are rounded for confidentiality of taxpayer data. Married is taken from an individual's filing status. Any Children is an indicator for if a household claimed any dependents in that year. Household Filed denotes that an individual or their spouse filed an Individual Tax Return in that tax year (Form-1040). Household AGI is the adjusted gross income drawn directly from the Individual Tax Return. Individual Income additionally incorporates non-filing earnings by summing information returns (e.g. W-2s, 1099s, etc.) and divides AGI in half for married filing jointly individuals. Wage job is an indicator for receiving a W-2. Wages is the sum of wages across all W-2 forms received by an individual. Spouse's Wages is the sum of wages across all W-2 forms received by an individual; this value is 0 if a spouse has no wages or an individual does not have a spouse, and is missing for non-filers. Schedule C Profit/Loss denotes the amount of profit/loss claimed on Sch C. Schedule C (HH) is an indicator for either the individual or spouse having filed Schedule C for income earned through a sole-proprietorship. Gig Job is an indicator for having an earnings from gig work. Student is an indicator for having an eligible tuition payment at a post-secondary institution. Has SSDI is an indicator for receiving Social Security Disability Insurance (Form 1099-SSA). Has SS Income is an indicator for withdrawing Social Security Retirement Income (Form 1099-SSA). Claimed EITC (HH) is an indicator that a Household claimed the EITC in that tax year.

Table 4: Short-Run Effects on Labor Supply, Income, and Social Insurance Receipt
(Prime-Age Workers)

VARIABLES	(1) Gig Year (x100)	(2) Gig Earnings	(3) Individual Income	(4) HH AGI	(5) Wages	(6) Wage Job (x100)
	Short Run (First Post Year)					
Post	0.00469*	-0.461**	-3,964***	-4,932***	-11,214***	-1.204***
	(0.00271)	(0.220)	(110.9)	(169.5)	(132.5)	(0.181)
Post x Gig Intensity	-0.214***	-7.021***	-994.7**	208.4	-770.6	-2.685***
	(0.0216)	(2.004)	(451.6)	(688.5)	(533.2)	(0.748)
Post x High	-0.727***	-46.19***	-1,394***	-2,604***	-237.8	0.236
	(0.0664)	(6.793)	(405.1)	(634.8)	(490.6)	(0.730)
Post x Gig Intensity x High	10.51***	620.3***	3,118***	2,573	1,835	1.450
	(0.444)	(48.90)	(1,039)	(1,616)	(1,211)	(1.847)
Observations (Unweighted)	3,031,317	3,031,317	3,031,317	2,750,404	3,031,317	3,031,317
Observations (Weighted)	46,850,202	46,850,202	46,850,202	42,716,803	46,850,202	46,850,202
R-squared	0.251	0.232	0.811	0.845	0.804	0.442
Pre-Period Dep Var Mean	0.01	0.32	32,036	45,178	33,097	92.8
Pre-Period Dep Var SD	0.77	93.24	25,414	39,679	29,275	25.9

Notes: Results presented are for the subsample of prime-age workers, those ages 25-54 at the time of UI receipt. Post UI, $k \geq 0$, indicate years following (and including) UI receipt. In these short-run specifications, Post is restricted to the year of UI receipt. Gig Intensity is a measure, between 0 and 1, of the degree of gig availability in the county in which an individual lives in at the time of unemployment insurance receipt and is fixed within individual. High is an indicator variable denoting that an individual is in the high predicted gig propensity sample. Regression includes individual fixed effects, county-by-year FEs, and age FEs. Data drawn around UI recipients first UI event in the period 2008-2015 and includes observations from tax years 2005-2017. Top 1% of wages and the top and bottom 1% of income and AGI are winsorized. All dollar values are inflation adjusted to 2017 dollars using CPI-U. Robust standard errors clustered by individual in parentheses ($^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$).

Table 5: Long-Run Effects on Labor Supply, Income, and Social Insurance Receipt
(Prime-Age Workers)

VARIABLES	(1) Gig Year (x100)	(2) Gig Earnings	(3) Individual Income	(4) HH AGI	(5) Wages	(6) Wage Job (x100)
	Long Run (Two-Four Years Post)					
Post	0.00878	-2.163	-7,705***	-8,025***	-13,963***	-14.78***
	(0.0116)	(1.808)	(165.6)	(263.0)	(194.1)	(0.276)
Post x Gig Intensity	0.0647	-22.83***	687.4	-109.8	1,604***	5.939***
	(0.0580)	(7.774)	(493.0)	(801.5)	(564.3)	(0.715)
Post x High	2.090***	112.9***	432.6	-630.2	774.6	-0.795
	(0.140)	(21.88)	(483.9)	(814.5)	(589.0)	(0.829)
Post x Gig Intensity x High	19.82***	2,831***	-2,478*	-4,847**	-3,951***	-4.542**
	(0.873)	(167.5)	(1,352)	(2,306)	(1,523)	(2.252)
Observations (Unweighted)	4,193,859	4,193,859	4,193,859	3,739,463	4,193,859	4,193,859
Observations (Weighted)	65,184,888	65,184,888	65,184,888	58,168,178	65,184,888	65,184,888
R-squared	0.274	0.265	0.721	0.773	0.708	0.406
Pre-Period Dep Var Mean	0.01	0.32	32,036	45,178	33,097	92.8
Pre-Period Dep Var SD	0.77	93.24	25,414	39,679	29,275	25.9

Notes: Results presented are for the subsample of prime-age workers, those ages 25-54 at the time of UI receipt. Post UI, $k \geq 0$, indicate years following (and including) UI receipt. In these long-run specifications, Post is restricted to the long-run post years, two to four years after UI receipt. Gig Intensity is a measure, between 0 and 1, of the degree of gig availability in the county in which an individual lives in at the time of unemployment insurance receipt and is fixed within individual. High is an indicator variable denoting that an individual is in the high predicted gig propensity sample. Regression includes individual fixed effects, county-by-year FEs, and age FEs. Data drawn around UI recipients first UI event in the period 2008-2015 and includes observations from tax years 2005-2017. Top 1% of wages and the top and bottom 1% of income and AGI are winsorized. All dollar values are inflation adjusted to 2017 dollars using CPI-U. Robust standard errors clustered by individual in parentheses ($^{***}p < 0.01$,$^{**}p < 0.05$,$^{*}p < 0.1$).

Table 6: Pre-UI Summary Statistics

(Older Workers)

	Mean	Std Dev	P10	Median	P90
Female	0.17	0.37			
Age	56	4	52	55	61
Married	0.53	0.50			
Any Children	0.30	0.46			
Household Filed	0.94	0.23			
Household AGI (2017 $)	65,928	48,402	16,500	53,500	133,300
Individual Income (2017 $)	41,461	29,090	9,400	36,300	79,600
Wage Job	0.90	0.30			
Wages (2017 $)	43,706	34,507	200	37,700	89,400
Spouse's Wages (2017 $)	15,029	25,376	0	0	53,500
Schedule C Profit/Loss (2017 $)	714	5,591	0	0	3300
Schedule C (HH)	0.28	0.45			
Gig Year	0.00	0.01			
Student	0.04	0.20			
Has SSDI	0.01	0.10			
Has SS Income	0.02	0.14			
Claimed EITC (HH)	0.14	0.35			

Notes: Sample is restricted to the older workers subsample, those ages 55-69 at the time of UI receipt. Summary statistics are for the three years prior to UI receipt. P10 and P90 represent the 10th and 90th percentile values of the corresponding variables. All P10, Median, and P90 values are rounded for confidentiality of taxpayer data. Married is taken from an individual's filing status. Any Children is an indicator for if a household claimed any dependents in that year. Household Filed denotes that an individual or their spouse filed an Individual Tax Return in that tax year (Form-1040). Household AGI is the adjusted gross income drawn directly from the Individual Tax Return. Individual Income additionally incorporates non-filing earnings by summing information returns (e.g. W-2s, 1099s, etc.) and divides AGI in half for married filing jointly individuals. Wage job is an indicator for receiving a W-2. Wages is the sum of wages across all W-2 forms received by an individual. Spouse's Wages is the sum of wages across all W-2 forms received by an individual; this value is 0 if a spouse has no wages or an individual does not have a spouse, and is missing for non-filers. Schedule C Profit/Loss denotes the amount of profit/loss claimed on Sch C. Schedule C (HH) is an indicator for either the individual or spouse having filed Schedule C for income earned through a sole-proprietorship. Gig Job is an indicator for having any earnings from gig work. Student is an indicator for having an eligible tuition payment at a post-secondary institution. Has SSDI is an indicator for receiving Social Security Disability Insurance (Form 1099-SSA). Has SS Income is an indicator for withdrawing Social Security Retirement Income (Form 1099-SSA). Claimed EITC (HH) is an indicator that a Household claimed the EITC in that tax year.

Table 7: Short-Run Effects on Labor Supply, Income, and Social Insurance Receipt
(Older Workers)

VARIABLES	(1) Gig Year (x100)	(2) Gig Earnings	(3) Individual Income	(4) HH AGI	(5) Wage Job (x100)	(6) Has SSDI (x100)	(7) Has Soc Sec Ret (x100)
	Short Run (First Post Year)						
Post	0.0588***	3.601**	-3,884***	-4,493***	-15,024***	1.162***	1.540***
	(0.0155)	(1.575)	(570.1)	(896.1)	(730.2)	(0.277)	(0.468)
Post x Gig Intensity	-0.375***	-25.79***	659.8	2,325	-1,280	-0.0532	1.333
	(0.0811)	(7.832)	(1,856)	(2,960)	(2,499)	(0.938)	(1.757)
Post x High	-1.434***	-112.3***	-2,475	-3,425	-111.3	0.640	2.774
	(0.346)	(34.13)	(1,883)	(2,635)	(2,654)	(1.191)	(2.142)
Post x Gig Intensity x High	16.23***	1,233***	4,174	4,242	5,778	-2.570	-1.285
	(2.205)	(205.6)	(4,675)	(7,776)	(7,595)	(2.495)	(5.406)
Observations (Unweighted)	165,746	165,746	165,746	154,771	165,746	165,746	165,746
Observations (Weighted)	2,697,869	2,697,869	2,697,869	2,547,007	2,697,869	2,697,869	2,697,869
R-squared	0.303	0.381	0.852	0.880	0.835	0.809	0.746
Pre-Period Dep Var Mean	0.01	0.48	42,397	66,580	44,222	1.09	3.20
Pre-Period Dep Var SD	0.82	175.88	28,916	48,532	34,283	10.38	17.60

Notes: Sample is restricted to the older workers subsample, those ages 55-69 at the time of UI receipt. Post UI, $k \geq 0$, indicate years following (and including) UI receipt. In these short-run specifications, Post is restricted to the year of UI receipt. Gig Intensity is a measure, between 0 and 1, of the degree of gig availability in the county in which an individual lives in at the time of unemployment insurance receipt and is fixed within individual. High is an indicator variable denoting that an individual is in the high predicted gig propensity sample. Regression includes individual fixed effects, county-by-year FEs, and age FEs. Data drawn around UI recipients first UI event in the period 2008-2015 and includes observations from tax years 2005-2017. Top 1% of wages and the top and bottom 1% of income and AGI are winsorized. All dollar values are inflation adjusted to 2017 dollars using CPI-U. Robust standard errors clustered by individual in parentheses ($^{***}p < 0.01$,$^{**}p < 0.05$,$^{*}p < 0.1$).

Table 8: Long-Run Effects on Labor Supply, Income, and Social Insurance Receipt
(Older Workers)

VARIABLES	(1) Gig Year (x100)	(2) Gig Earnings	(3) Individual Income	(4) HH AGI	(5) Wage Job (x100)	(6) Has SSDI (x100)	(7) Has Soc Sec Ret (x100)
	Long Run (Two-Four Years Post)						
Post	0.200***	37.00***	-10,722***	-10,958***	-24,230***	6.250***	6.238***
	(0.0649)	(12.91)	(852.0)	(1,351)	(1,092)	(0.699)	(0.868)
Post x Gig Intensity	0.452	51.76	-1,871	-9,020***	-1,986	-8.834***	6.556***
	(0.285)	(56.74)	(2,084)	(3,394)	(2,586)	(2.095)	(2.429)
Post x High	1.150*	-170.4	-2,681	-4,474	243.4	-0.759	0.565
	(0.603)	(108.0)	(2,030)	(3,185)	(2,716)	(1.624)	(2.427)
Post x Gig Intensity x High	33.09***	6,423***	6,757	10,598	11,647	-6.227*	-4.390
	(4.017)	(768.3)	(5,725)	(10,830)	(8,832)	(3.316)	(6.277)
Observations (Unweighted)	228,361	228,361	228,361	205,439	228,361	228,361	228,361
Observations (Weighted)	3,769,690	3,769,690	3,769,690	3,386,606	3,769,690	3,769,690	3,769,690
R-squared	0.328	0.326	0.784	0.828	0.752	0.632	0.819
Pre-Period Dep Var Mean	0.01	0.48	42,397	66,580	44,222	1.09	3.20
Pre-Period Dep Var SD	0.82	175.88	28,916	48,532	34,283	10.38	17.60

Notes: Sample is restricted to the older workers subsample, those ages 55-69 at the time of UI receipt. Post UI, $k \geq 0$, indicate years following UI receipt. In these long-run specifications, Post is restricted to the long-run post years, two to four years after UI receipt. Gig Intensity is a measure, between 0 and 1, of the degree of gig availability in the county in which an individual lives in at the time of unemployment insurance receipt and is fixed within individual. High is an indicator variable denoting that an individual is in the high predicted gig propensity sample. Regression includes individual fixed effects, county-by-year FEs, and age FEs. Data drawn around UI recipients first UI event in the period 2008-2015 and includes observations from tax years 2005-2017. Top 1% of wages and the top and bottom 1% of income and AGI are winsorized. All dollar values are inflation adjusted to 2017 dollars using CPI-U. Robust standard errors clustered by individual in parentheses ($^{***}p < 0.01$,$^{**}p < 0.05$,$^{*}p < 0.1$).

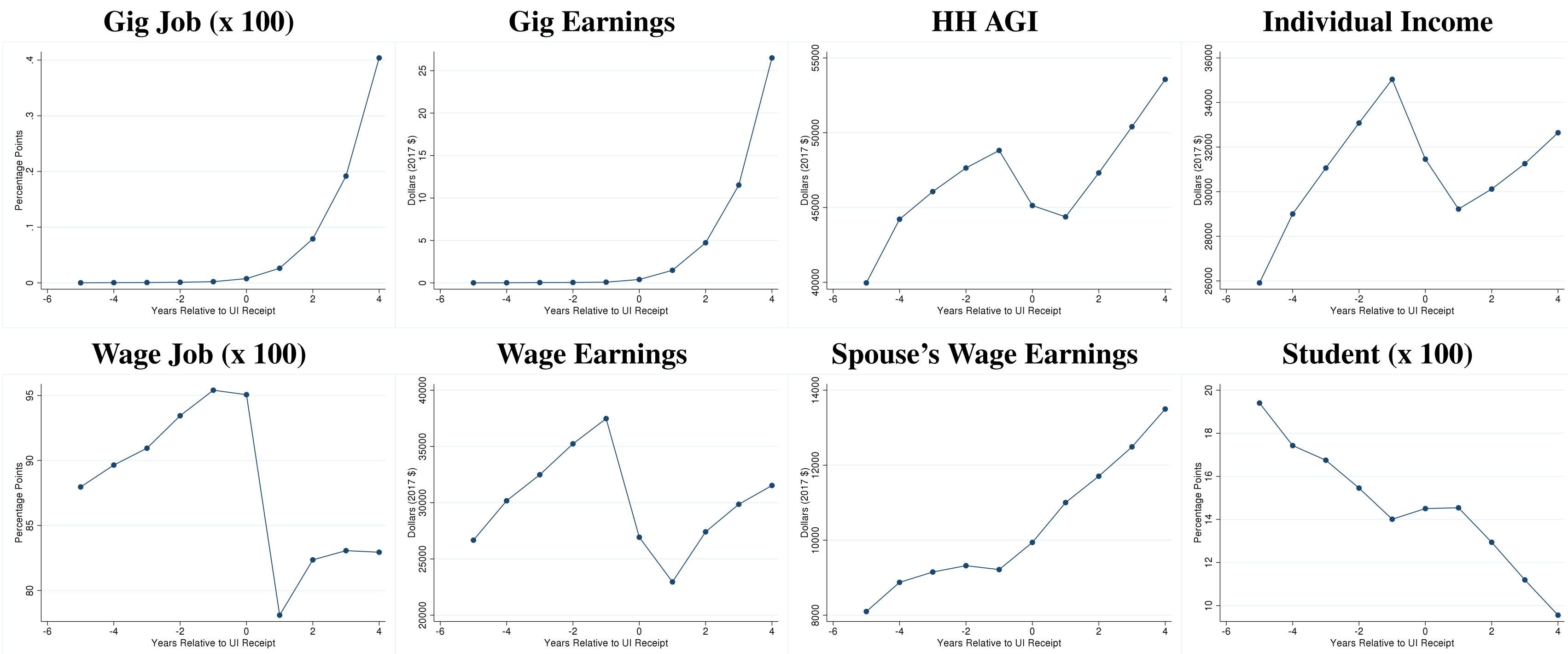
FOR ONLINE PUBLICATION:

Availability of the Gig Economy and Long Run Labor Supply Effects for the Unemployed

(Emilie Jackson)

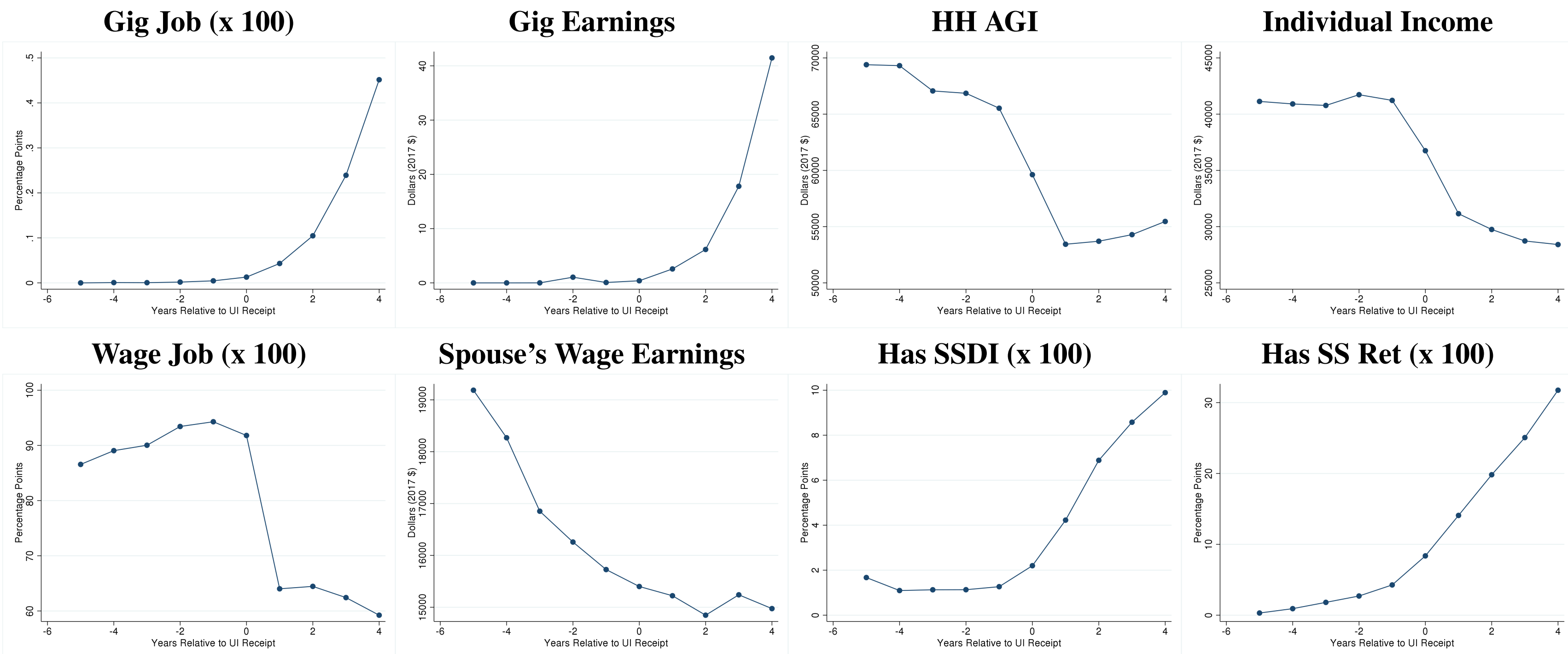
Appendix A Figures and Tables

Figure A1: Summary of Key Outcome Variables by Year Relative to UI Receipt
(Prime-Age Workers)



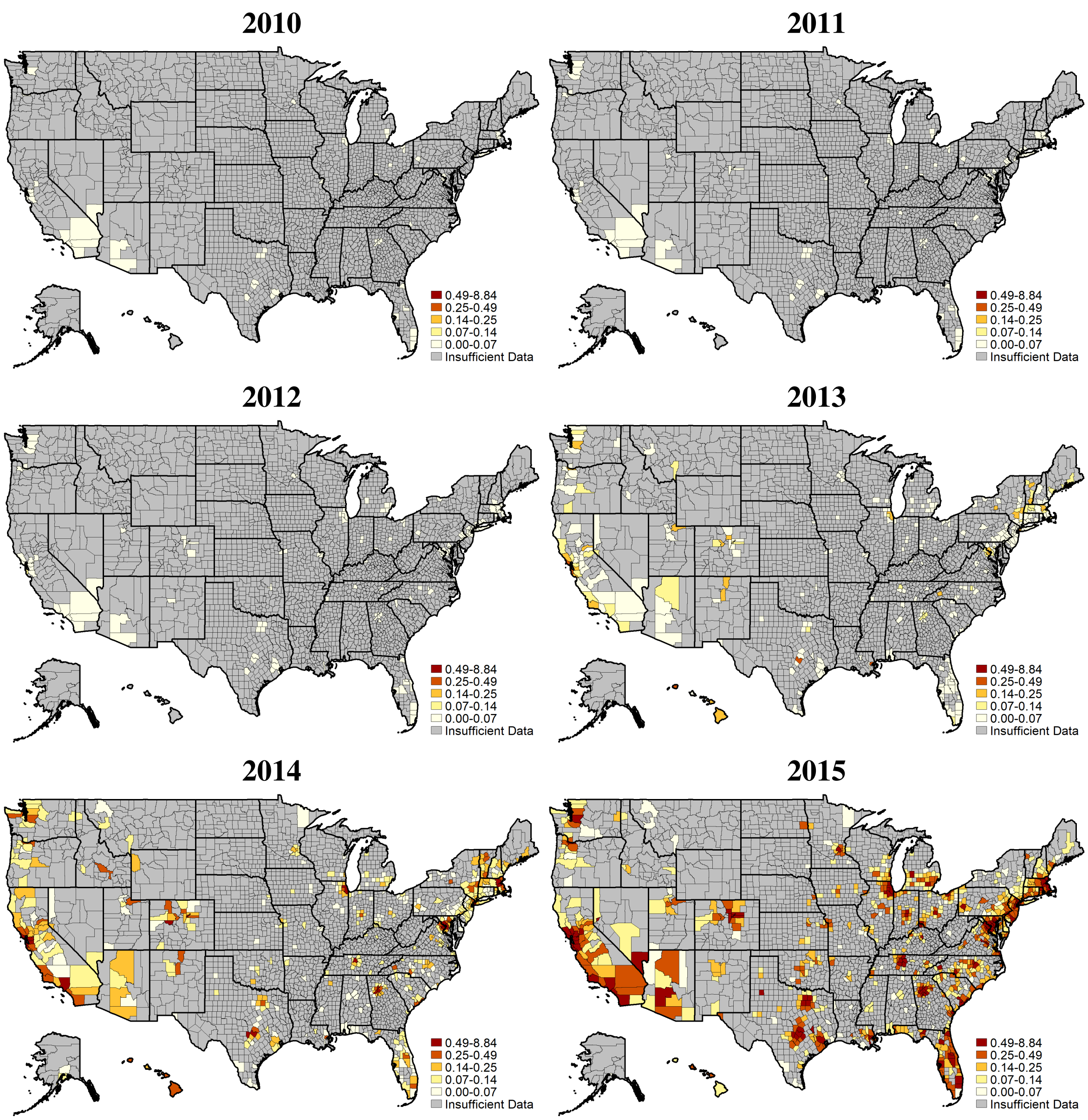
Notes: Averages of each outcome are plotted by year relative to UI receipt for individuals who become unemployed in a county and year where there are no gig platforms available. Gig Job denotes having any income from gig work in that tax year. Gig Earnings are the sum of all earnings earned in the gig economy. Household AGI is the adjusted gross income drawn directly from the Individual Tax Return. Individual Income additionally incorporates non-filing earnings by summing information returns (e.g. W-2s, 1099s, etc.) and divides AGI in half for married filing jointly individuals. Wage job indicates receiving a W-2 in a given year. Wage Earnings are the sum of all W-2 wages in a given year. Spouse's Wage Earnings are the sum of all W-2 wages of a spouse and are restricted to filers. Student is an indicator for having an eligible tuition payment made for post-secondary schooling (Form 1098-T).

Figure A2: Summary of Key Outcome Variables by Year Relative to UI Receipt
(Older Workers)



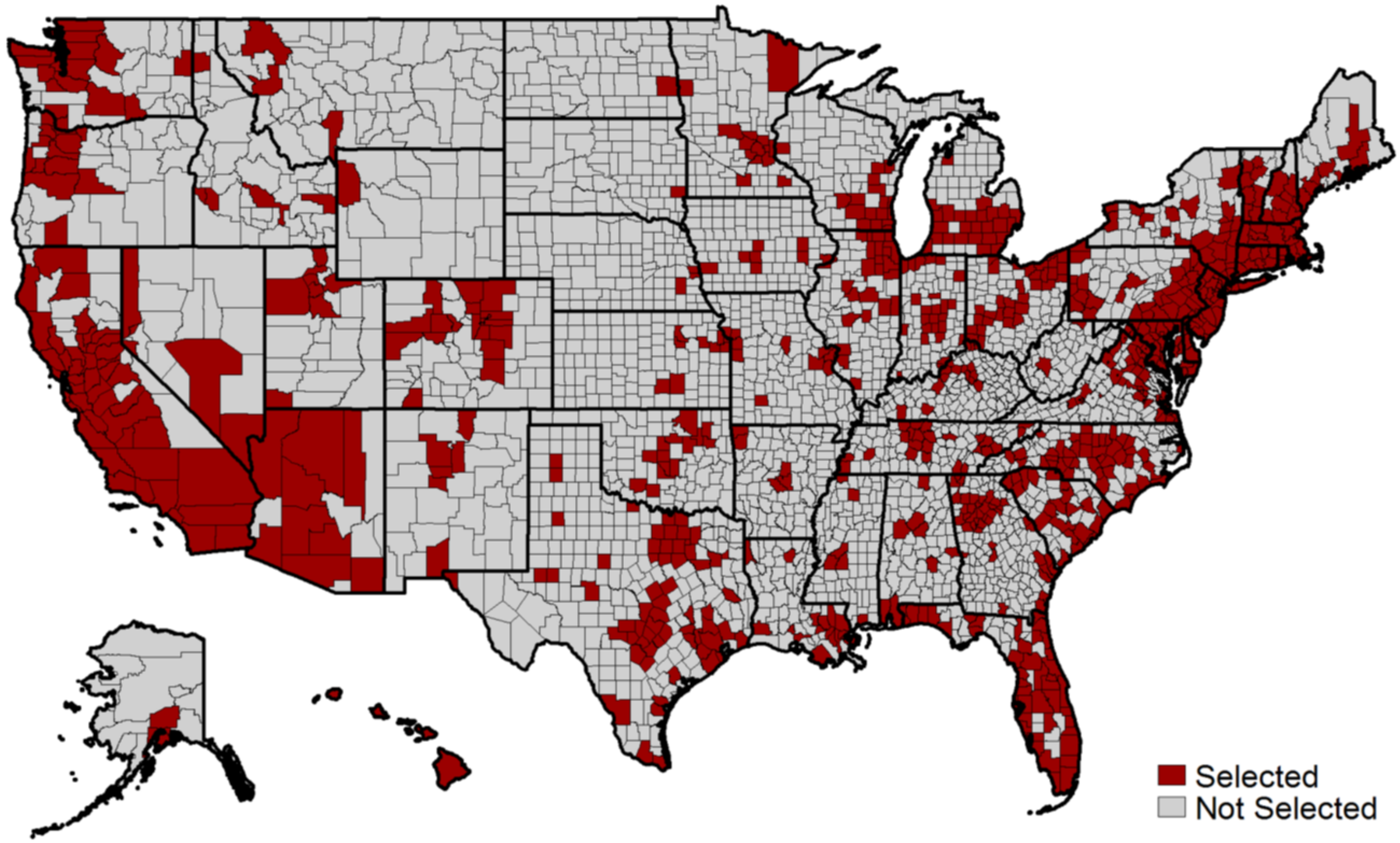
Notes: Averages of each outcome are plotted by year relative to UI receipt for individuals who become unemployed in a county and year where there are no gig platforms available. Gig Job denotes having any income from gig work in that tax year. Gig Earnings are the sum of all earnings earned in the gig economy. Household AGI is the adjusted gross income drawn directly from the Individual Tax Return. Individual Income additionally incorporates non-filing earnings by summing information returns (e.g. W-2s, 1099s, etc.) and divides AGI in half for married filing jointly individuals. Wage job indicates receiving a W-2 in a given year. Spouse's Wage Earnings are the sum of all W-2 wages of a spouse and are restricted to filers. Has SSDI is an indicator for receiving Social Security Disability Insurance (Form 1099-SSA). Has SS Ret Income is an indicator for claiming Social Security Retirement Income (Form 1099-SSA).

Figure A3: Percent of a County's Working Age Population (15-64) with any Gig Work by Year



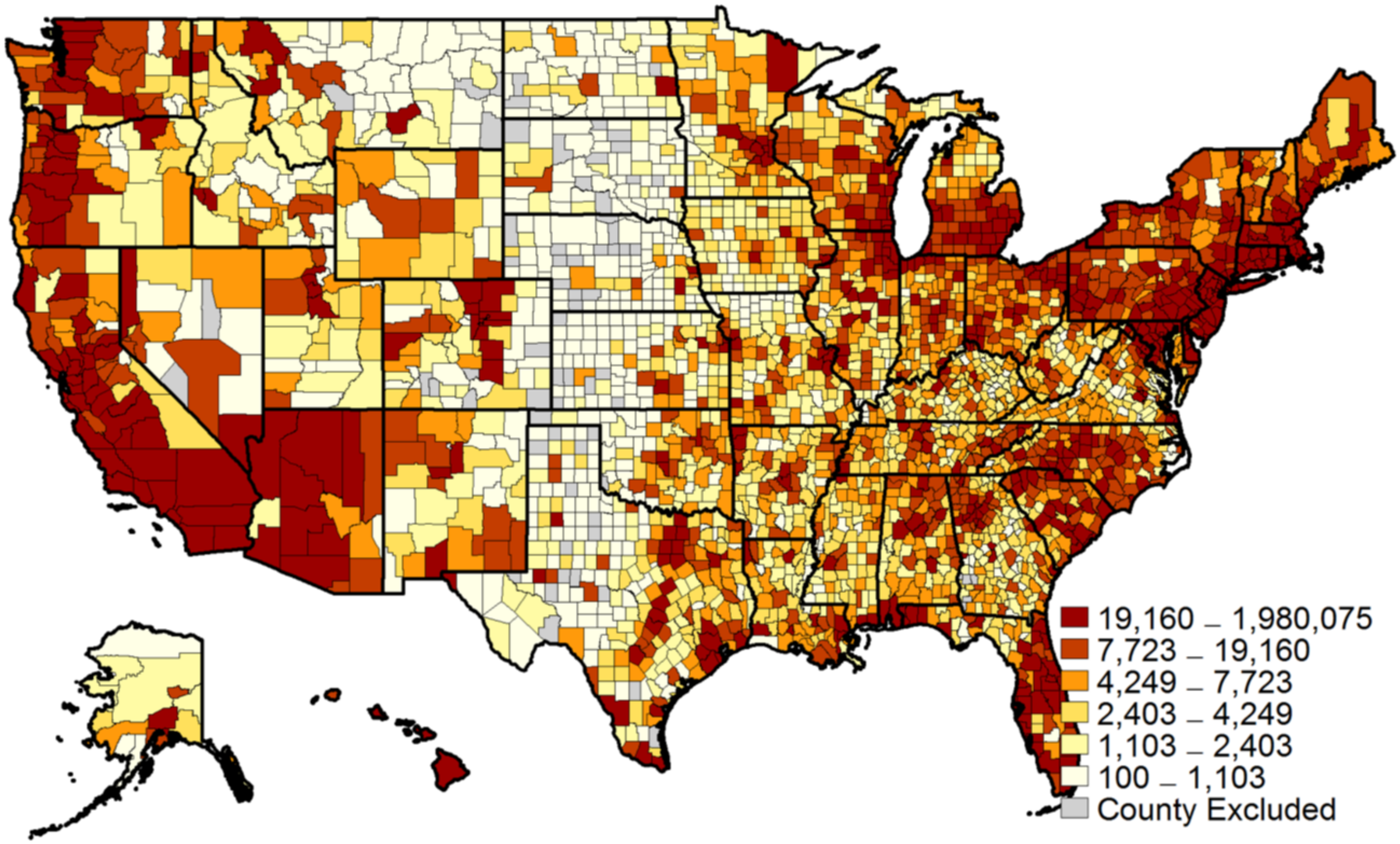
Notes: The above maps illustrate the geographic variation in gig platform availability at a given point in time across counties. Second, they illustrate variation within a county over time in the prevalence of gig work, as measured in the percent of the counties working age population with any amount of gig earnings in that year. "Insufficient Data" means that a cell has fewer than 30 observations with any gig work and are suppressed; predominantly, these consist of zeros rather then suppressed data points.

Figure A4: County Selection



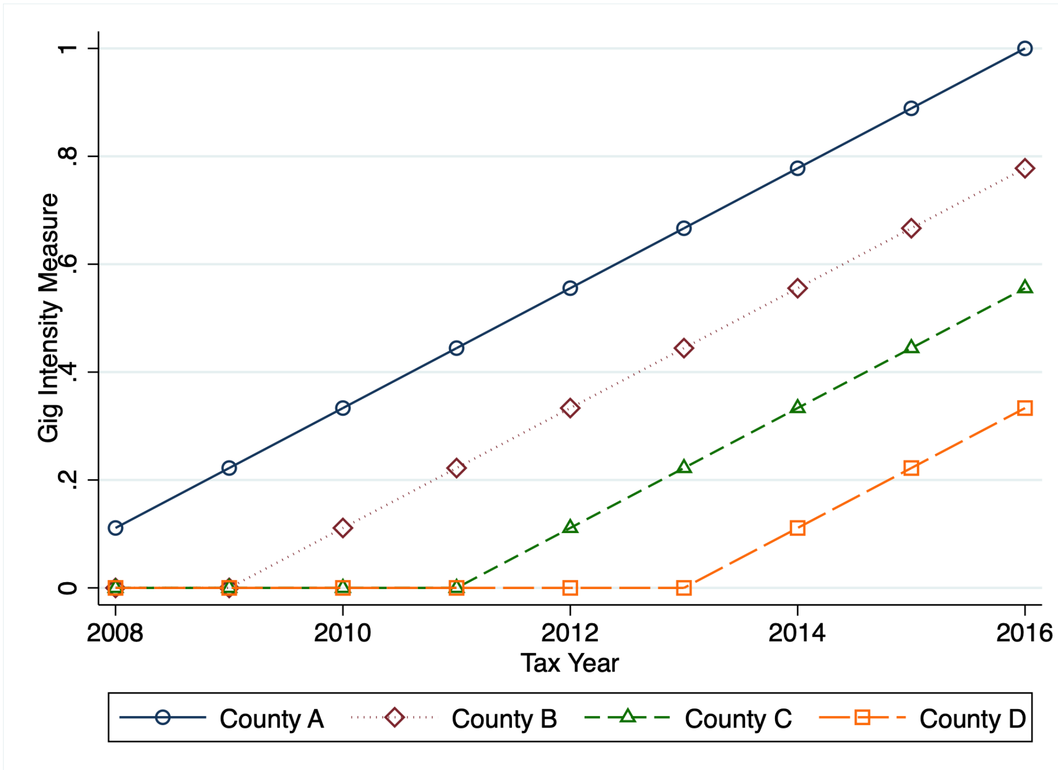
Notes: Counties in dark red had gig platforms enter by 2015. All individuals who become unemployed outside of these counties are excluded from the analysis sample.

Figure A5: UI Distribution by County



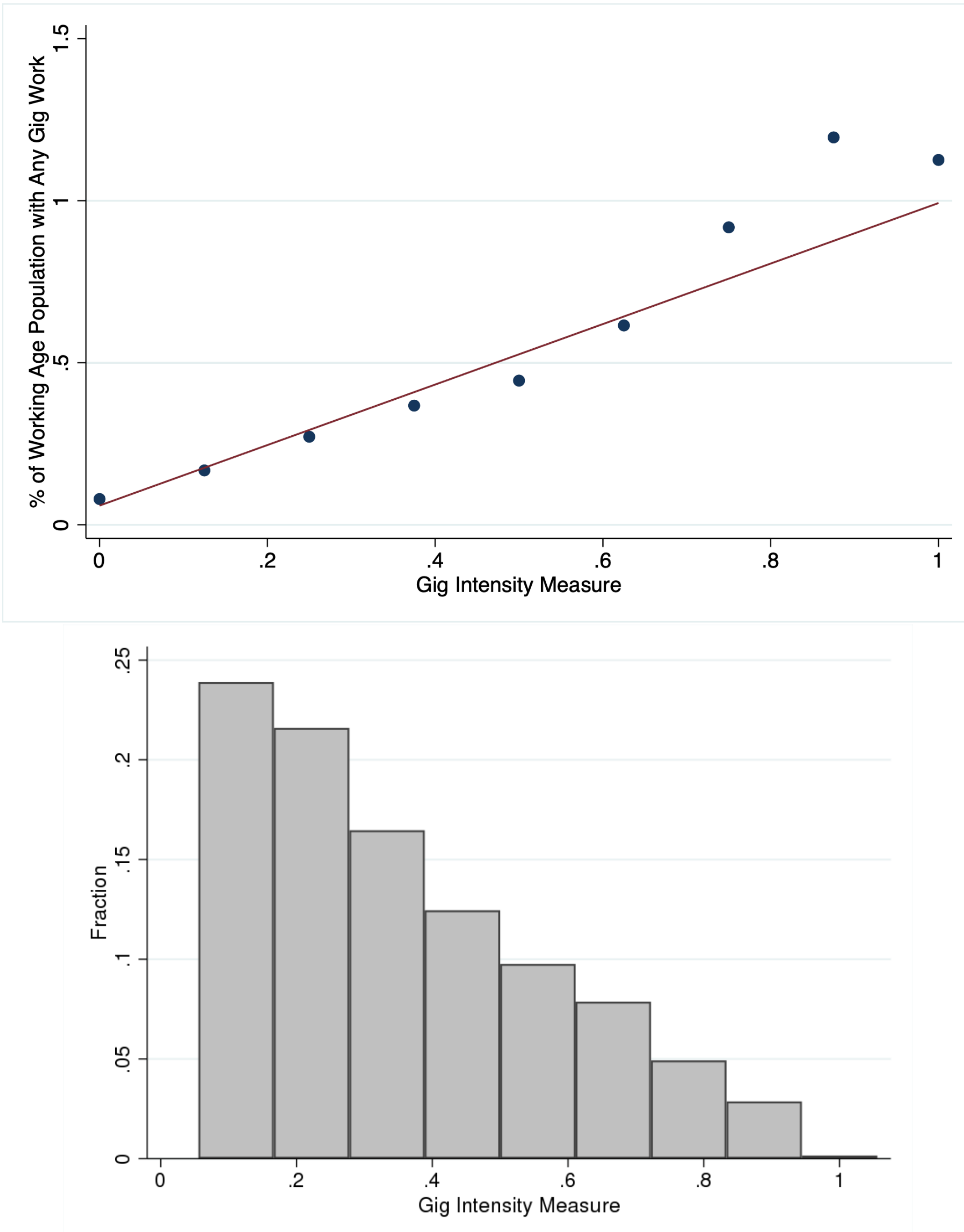
Notes: Counts indicate the number of UI events between 2008-2015 by each county.

Figure A6: Illustration of Gig Treatment Intensity Variable



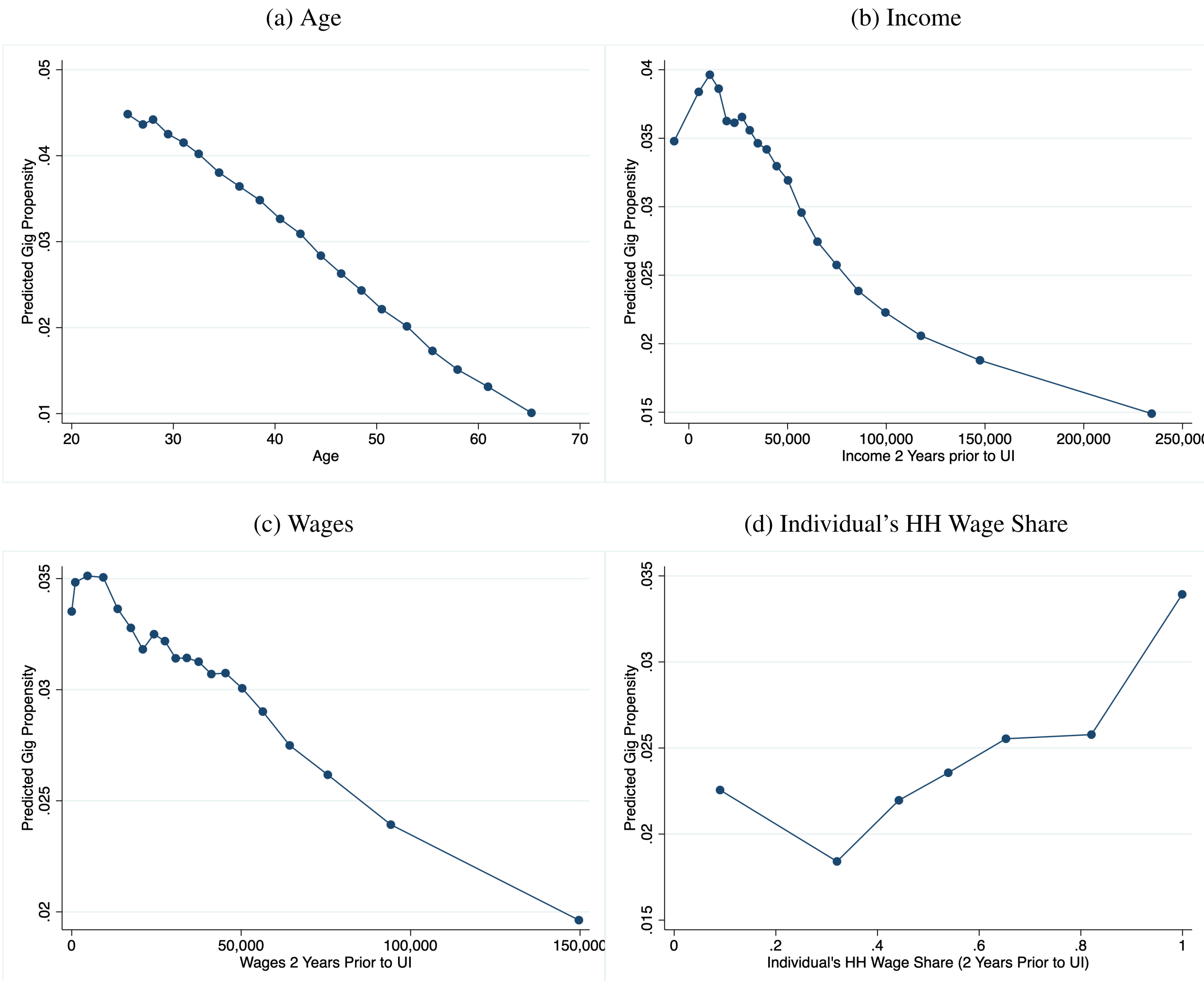
Notes: My 'Gig Intensity Measure' captures the number of years gig platforms were available in a given county in each year and is scaled by $\frac{1}{9}$ —the maximum of years gig platforms were available at the time of job loss across all individuals in my analysis —to be a measure $\in [0,1]$. In this example, gig platforms first enter County A in 2008, County B in 2010, County C in 2012, and County D in 2014.

Figure A7: Linearity of Intensity Measure



Notes: Figure A7 plots the average, across counties, percent of the working age population with any amount of gig earnings in that county-year by my gig intensity measure. The bottom panel shows the distribution of my gig intensity measure across individuals in my sample.

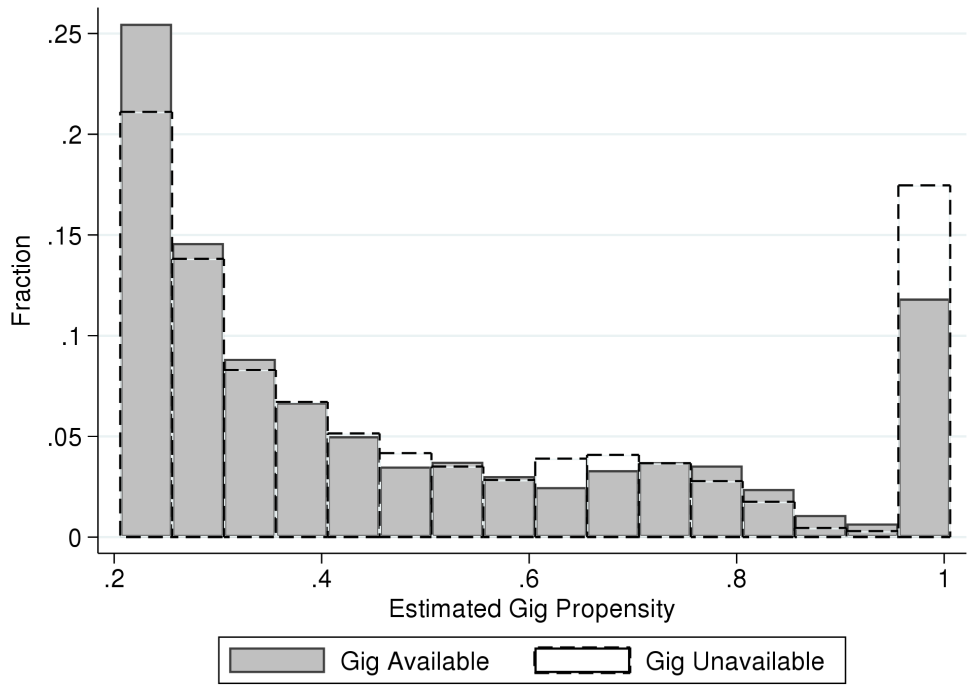
Figure A8: Predicted Gig Propensities with Respect to Key Predictors



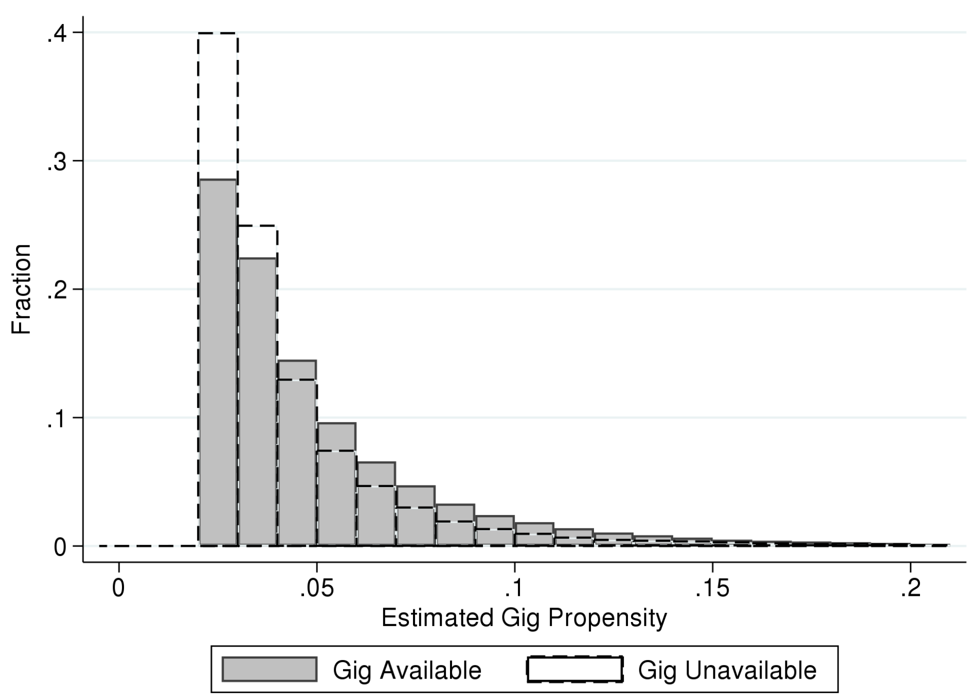
Notes: Age is at the time of UI receipt. Income is household AGI from Form 1040 for filers and the sum of information returns for non-filers (e.g. W-2s, 1099s, etc.). Wage Earnings are the sum of all W-2 wages. Individual household wage share is the an individual's wage earnings as a fraction of the sum of the individual's and spouse's wages.

Figure A9: Distribution of Gig Propensities by Gig Availability

(a) Among High-gig-propensity Individuals

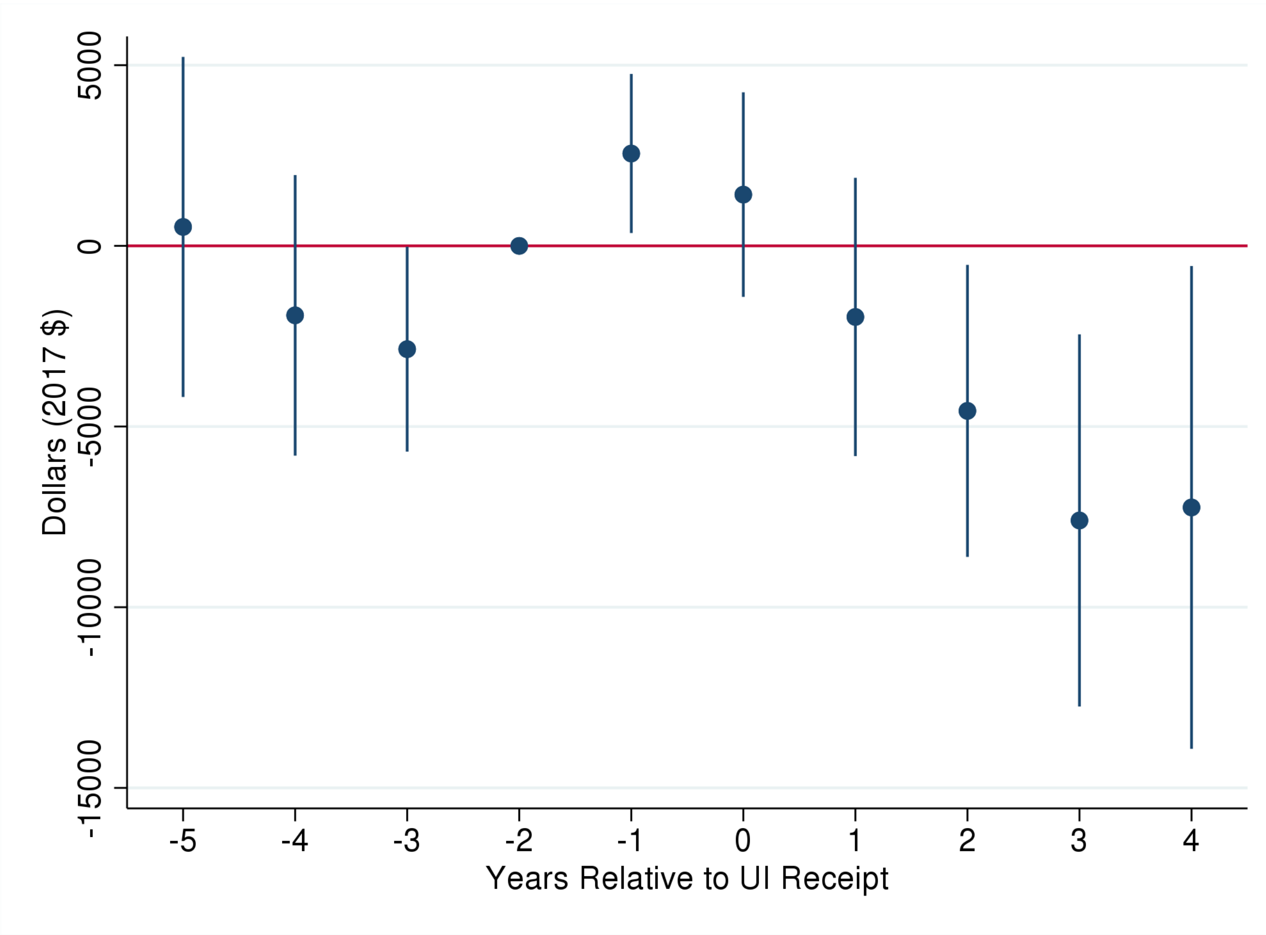


(b) Among Low-gig-propensity Individuals



Notes: High-gig-propensity individuals have predicted propensity values > 0.2 and low-gig-propensity individuals have predicted propensities between 0.02 and 0.20.

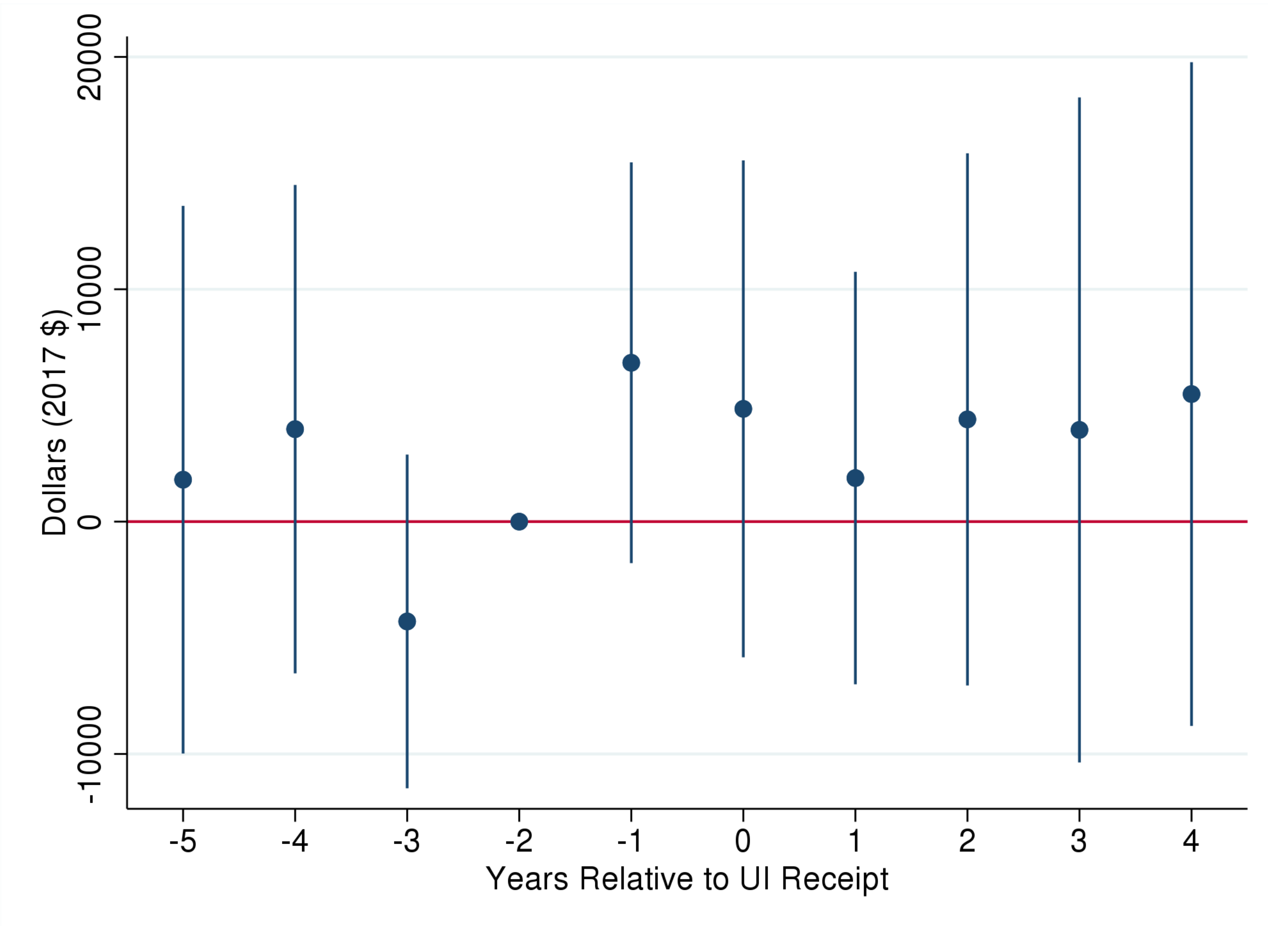
Figure A10: Yearly Coefficients for Household Adjusted Gross Income
(Prime-Age Workers)



Notes: Dependent variable is Household AGI (2017 $), and the top and bottom 1% of values are winsorized. Coefficient estimates for $T_{it}^{k} * G_i * H_i$ are plotted for each year in event time relative to event time k=-2. These estimates are interpreted as the effect of having the most gig availability at UI receipt compared to no gig availability among high-gig-propensity individuals, differencing out any changes that occur among the low-gig-propensity individuals, and each yearly coefficient is relative to two years prior to UI receipt. Sample balanced on event time $k \in [-3, 2]$. Regression includes individual FEs, county-by-year FEs, and age FEs. Data drawn around UI recipients first UI event in the period 2008-2015 and includes observations from 2005-2017. Robust standard errors clustered by individual.

Figure A11: Yearly Coefficients for Individual Income

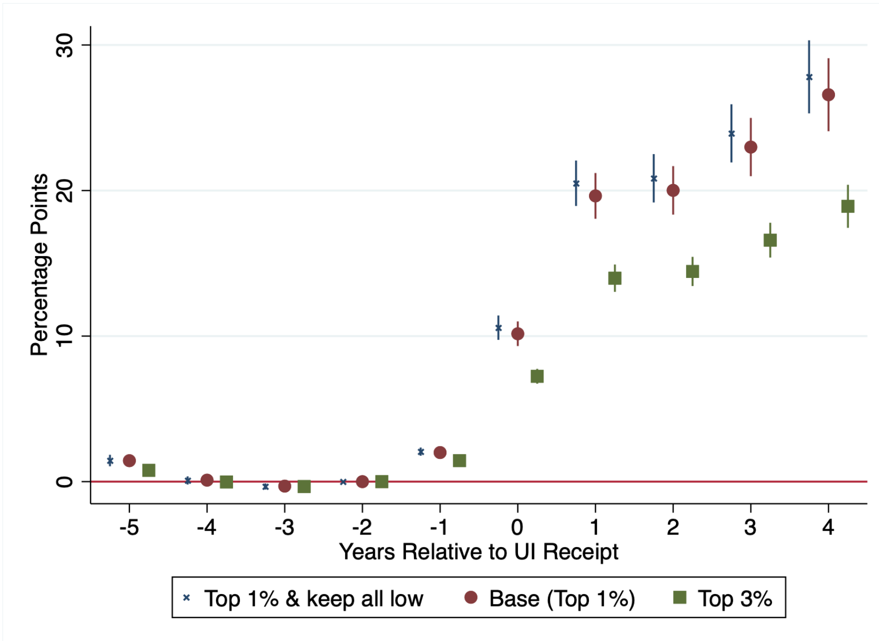
(Older Workers)



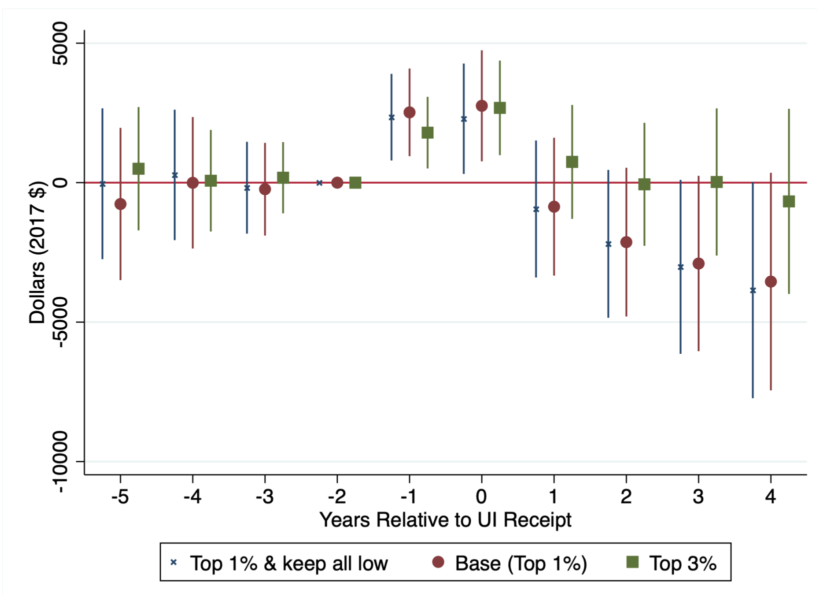
Notes: Dependent variable is individual income (2017 \$), and the top and bottom 1% of values are winsorized. Restricted to older workers, ages 55-69 at the time of UI receipt. Coefficient estimates for $T_{it}^{k} * G_i * H_i$ are plotted for each year in event time relative to event time k=-2. These estimates are interpreted as the effect of having the most gig availability at UI receipt compared to no gig availability among high-gig-propensity individuals, differencing out any changes that occur among the low-gig-propensity individuals, and each yearly coefficient is relative to two years prior to UI receipt. Sample balanced on event time $k \in [-3, 2]$. Regression includes individual FEs, county-by-year FEs, and age FEs. Data drawn around UI recipients first UI event in the period 2008-2015 and includes observations from 2005-2017. Robust standard errors clustered by individual.

Figure A12: Robustness to Definition of High and Low-gig-propensity
(Prime-Age Workers)

(a) Gig Job (x 100)

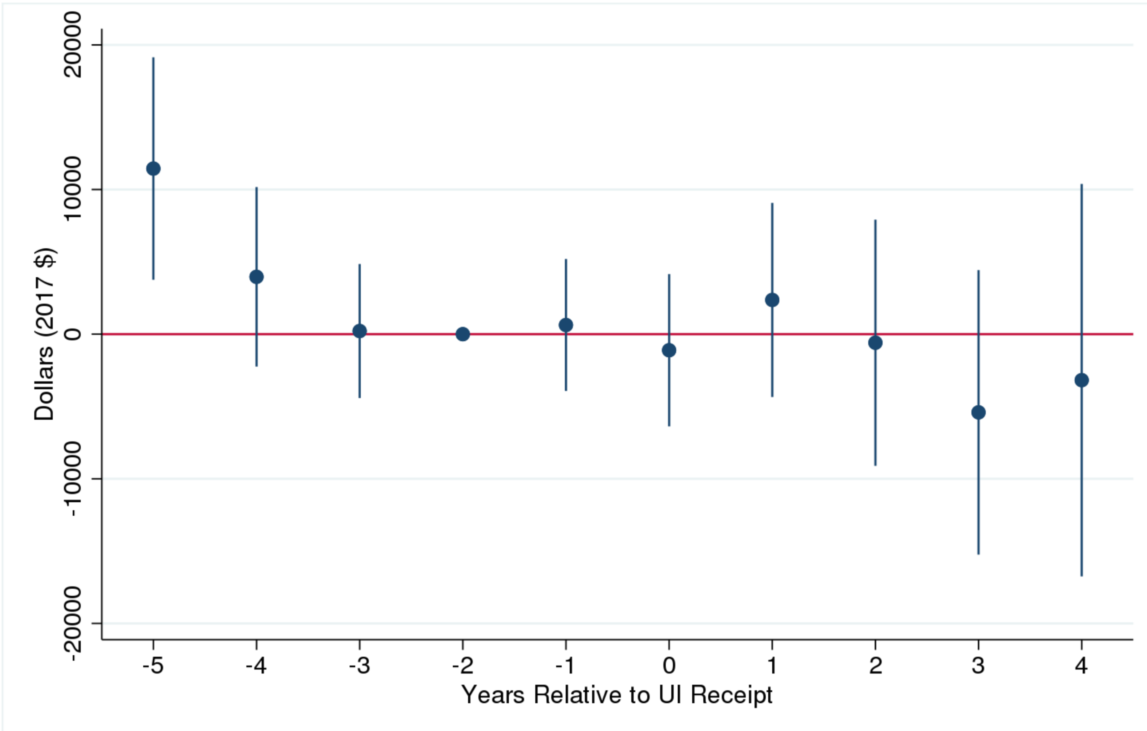


(b) Individual Income (2017 $)



Notes: In the top panel, the dependent variable is an indicator for having any gig work in a given year, in percentage points. In the bottom panel, the dependent variable is individual income (2017 $), and the top and bottom 1% of values are winsorized. Sample is restricted to prime-age workers, ages 25-54. Coefficient estimates for $T_{it}^k * G_i * H_i$ are plotted for each year in event time relative to event time k=-2. These estimates are interpreted as the effect of having the most gig availability at UI receipt compared to no gig availability among high-gig-propensity individuals, differencing out any changes that occur among the low-gig-propensity individuals, and each yearly coefficient is relative to two years prior to UI receipt. Sample balanced on event time $k \in [-3, 2]$. Regression includes individual FEs, county-by-year FEs, and age FEs. Data drawn around UI recipients first UI event in the period 2008-2015 and includes observations from 2005-2017. Robust standard errors clustered by individual.

Figure A13: Placebo Test for Individual Income (2017 $)
(Prime-Age Workers)



Notes: The dependent variable is individual income (2017 $), and the top and bottom 1% of values are winsorized. Sample is restricted to prime-age workers, ages 25-54. Coefficient estimates for $T_{it}^{k} * G_i * H_i$ are plotted for each year in event time relative to event time k=-2. These estimates are interpreted as the effect of having the most gig availability at UI receipt compared to no gig availability among high-gig-propensity individuals, differencing out any changes that occur among the low-gig-propensity individuals, and each yearly coefficient is relative to two years prior to UI receipt. Sample balanced on event time $k \in [-3, 2]$. Regression includes individual FEs, county-by-year FEs, and age FEs. Data drawn around UI recipients first UI event in the period 2002-2005 and includes observations from 1999-2006. Robust standard errors clustered by individual.

Table A1: Pooled Effects on Labor Supply, Income, and Social Insurance Receipt
(Prime-Age Workers)

VARIABLES	(1) Gig Year (x100)	(2) Gig Earnings	(3) Individual Income	(4) HH AGI	(5) Wages	(6) Wage Job (x100)
	Pooled (All Post Years)					
Post	-0.0358***	-1.408	-4,728***	-6,524***	-13,098***	-3.643***
	(0.00742)	(0.922)	(109.6)	(167.3)	(132.1)	(0.179)
Post x Gig Intensity	0.110***	-49.07***	64.91	-1,921***	-565.5	7.813***
	(0.0384)	(4.588)	(317.0)	(498.4)	(371.2)	(0.472)
Post x High	1.048***	63.29***	50.52	-1,041	700.8	-0.874
	(0.120)	(14.75)	(410.7)	(681.3)	(507.7)	(0.700)
Post x Gig Intensity x High	17.27***	1,948***	-853.3	-2,025	-2,124*	-1.921
	(0.752)	(101.4)	(1,091)	(1,812)	(1,246)	(1.784)
Observations (Unweighted)	5,586,081	5,586,081	5,586,081	5,004,336	5,586,081	5,586,081
Observations (Weighted)	86,843,796	86,843,796	86,843,796	77,627,370	86,843,796	86,843,796
R-squared	0.246	0.228	0.705	0.763	0.679	0.336
Pre-Period Dep Var Mean	0.01	0.32	32,036	45,178	33,097	92.8
Pre-Period Dep Var SD	0.77	93.24	25,414	39,679	29,275	25.9

Notes: Results presented are for the subsample of prime-age workers, those ages 25-54 at the time of UI receipt. Post UI, $k \geq 0$, indicate years following (and including) UI receipt. Gig Intensity is a measure, between 0 and 1, of the degree of gig availability in the county in which an individual lives in at the time of unemployment insurance receipt and is fixed within individual. High is an indicator variable denoting that an individual is in the high predicted gig propensity sample. Regression includes individual fixed effects, county-by-year FEs, and age FEs. Data drawn around UI recipients first UI event in the period 2008-2015 and includes observations from tax years 2005-2017. Top 1% of wages and the top and bottom 1% of income and AGI are winsorized. All dollar values are inflation adjusted to 2017 dollars using CPI-U. Robust standard errors clustered by individual in parentheses ($^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$).

Table A2: Pooled Effects on Labor Supply, Income, and Social Insurance Receipt

(Older Workers)

VARIABLES	(1) Gig Year (x100)	(2) Gig Earnings	(3) Individual Income	(4) HH AGI	(5) Wages	(6) Has SSDI (x100)	(7) Has Soc Sec Ret (x100)
	Pooled (All Post Years)						
Post	0.0413	13.40*	-4,817***	-6,373***	-17,384***	0.568	2.020***
	(0.0445)	(7.723)	(537.3)	(836.7)	(686.5)	(0.411)	(0.556)
Post x Gig Intensity	0.341*	-46.51	3,586***	3,457	637.8	-7.749***	1.886
	(0.189)	(30.91)	(1,367)	(2,142)	(1,781)	(1.215)	(1.536)
Post x High	0.584	-103.2	-2,077	-2,977	248.8	0.418	0.664
	(0.543)	(83.12)	(1,689)	(2,568)	(2,336)	(1.247)	(1.923)
Post x Gig Intensity x High	27.44***	4,395***	5,204	6,000	8,825	-5.896**	-2.877
	(3.564)	(563.8)	(4,404)	(7,799)	(7,230)	(2.420)	(5.334)
Observations (Unweighted)	303,549	303,549	303,549	273,582	303,549	303,549	303,549
Observations (Weighted)	5,000,406	5,000,406	5,000,406	4,504,347	5,000,406	5,000,406	5,000,406
R-squared	0.302	0.306	0.753	0.803	0.708	0.599	0.791
Pre-Period Dep Var Mean	0.01	0.48	42,397	66,580	44,222	1.09	3.20
Pre-Period Dep Var SD	0.82	175.88	28,916	48,532	34,283	10.38	17.60

Notes: Sample is restricted to the older workers subsample, those ages 55-69 at the time of UI receipt. Post UI, $k \geq 0$, indicate years following (and including) UI receipt. Gig Intensity is a measure, between 0 and 1, of the degree of gig availability in the county in which an individual lives in at the time of unemployment insurance receipt and is fixed within individual. High is an indicator variable denoting that an individual is in the high predicted gig propensity sample. Regression includes individual fixed effects, county-by-year FEs, and age FEs. Data drawn around UI recipients first UI event in the period 2008-2015 and includes observations from tax years 2005-2017. Top 1% of wages and the top and bottom 1% of income and AGI are winsorized. All dollar values are inflation adjusted to 2017 dollars using CPI-U. Robust standard errors clustered by individual in parentheses ($^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$).

Appendix B Data Appendix

B.1 The Gig Economy, Form 1099-MISC and Form 1099-K

Prior to the introduction of Form 1099-K in 2011, payments issued by the online gig platforms would only be found on 1099-MISCs. However, following the introduction of the 1099-K some platforms chose to start issuing 1099-Ks to report payments to workers.

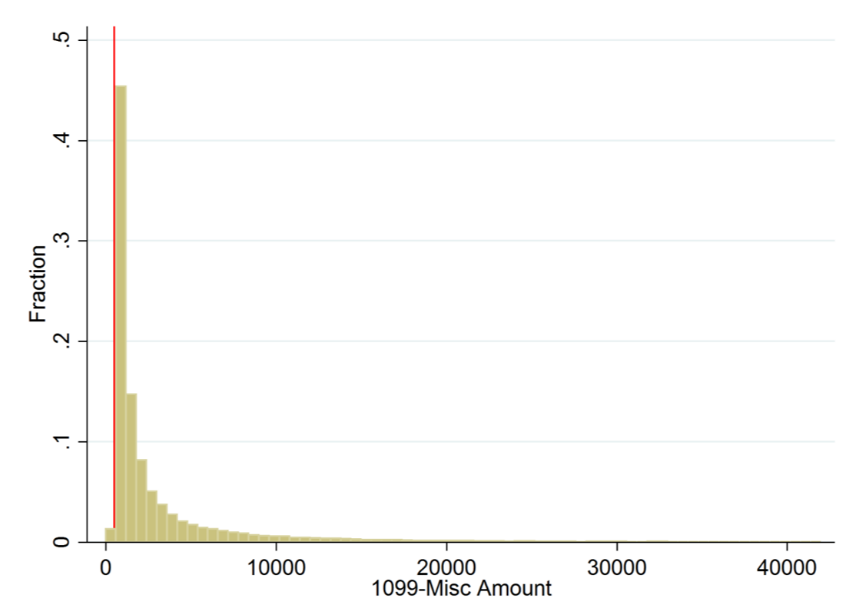
Complicating matters, there is no consistency across platforms in their decision of which form(s) to issue to their workers. Some firms may issue only a 1099-MISC while others issue only a 1099-K, and others may send both. One example of a scenario under which a platform might issue both forms would be if they reported payments from customers on Form 1099-K and reported bonuses or other incentive payments on Form 1099-MISC. Thus, I considered payments that are reported on both 1099-MISC and 1099-K from the list of online platform economy Employer Identification Numbers (EINs). The list of online gig platforms consists of approximately 50 labor based platforms and is drawn from online public lists.
1099-MISC: IRS form 1099-MISC reports miscellaneous income. Of particular relevance is income that is reported on line 7, non-employee compensation, which includes payments for services that an individual provides when the individual is not an employee. This broadly includes all income earned as an independent contractor. However, other sources of income may also be reported by a payer, which include but are not limited to: rents; prizes and awards; royalties; medical and health care payments; crop insurance proceeds; fishing boat proceeds. The relevant filing threshold requirement for non-employee compensation is 600$. Thus, for amounts of income earned above this threshold from a specific payer, the payer must fill out a 1099-MISC form denoting the income. The payer submits a copy of the form to both the IRS (directly) and to the payee. The payer's name and the payer's EIN (employer identification number) are required on the form, and thus can be used to distinguish between income earned through platforms classified as the online platform economy and other sources.

1099-K: IRS form 1099-K reports Payment Card and Third Party Network Transactions. In 2011, this form was introduced to increase compliance. Filing is required when total gross payments exceed \$20,000 and 200 transactions. While the threshold for 1099-K is high, many individuals within our identified gig population also received 1099-Ks even with income below these thresholds. I present the distribution of 1099-K by dollar amounts among gig workers in Figure B1.

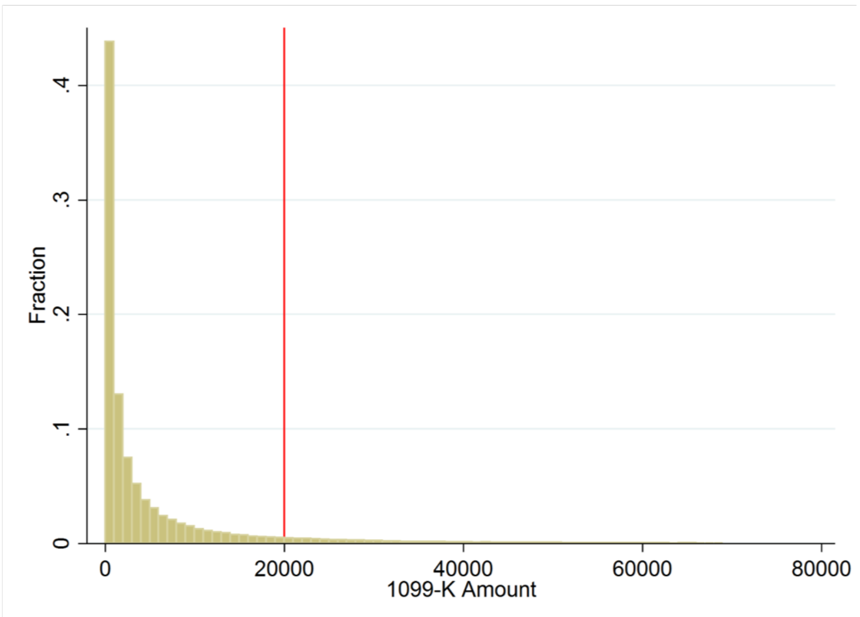
Schedule C: Schedule reports *Profit or Loss from Business (Sole Proprietorship)*. When filing, individuals self-report their "principal business or profession". For the small subset of individuals who do not receive either a 1099-MISC nor a 1099-K, I utilize information in these text strings to identify individuals who work in the online platform economy.

Figure B1: Distribution of 1099 $ Amounts

(a) 1099MISC



(b) 1099K



Notes: This Figure presents the distribution of the dollar amounts that an individual receives on a 1099-MISC (Panel A) and 1099-K (Panel B) related to gig work. The sample is restricted to individuals who are identified as Gig Participants. The width of each bin is $600 (Panel A) and $1000 (Panel B). The filing requirements are indicated with the red line at 600$ (Panel A) and 20,000$ (Panel B).

B.2 Data Cleaning

As the data are arranged and stored with the purpose of tax administration rather than research, there are several key decisions that have to be made in cleaning the data. First, each individual or entity is identified by a Taxpayer Identification Numbers (TIN). For individuals this is typically a social security number (SSN), but may also be an individual taxpayer identification number (ITIN) for non-resident or resident aliens, or even in the case of sole-propietorships an Employer Identification Number (EIN).

EINs typically represent what we think of as a business, but in the case of sole-proprietorships when there is no legal distinction between the individual and the their business entity. However, not all sole-proprietors register for an EIN. Thus, they may file and/or receive their information returns under either their SSN or their EIN.

B.3 Sample Construction

Among this set of UI recipients, I draw a stratified random sample based on the last four digits of an individual's SSN. I stratify individuals based on whether I ever observe an individual with any gig work in 2005-2017, and over-sample from the group of ever gig workers since gig work is an outcome of interest and accounts for a smaller fraction of the individuals in my sample. Specifically, I take a 1% random sample of individuals that I never observe taking up gig work and a 100% sample of individuals that I ever observe with any gig work, regardless of whether it is in the period around unemployment that I examine. I use sampling weights to account for this stratified random sampling methodology in all analyses.

I present weighted population level counts in Table B1 to provide a sense of how each sample restriction leads to the final set of observations. The overall counts restrict to individuals between the ages of 14-69 at UI receipt, to exclude outlying or potentially erroneous observations and I also drop all individuals who die during the period three years post-UI, to keep the sample balanced. From the overall sample of individuals, I split the sample into two sub-groups based on their age at UI receipt: prime-age workers, ages 25-54, and older workers, ages 55-69. These are the two key groups that I will focus on in this sample.

Between 2005-2017, there are 68 million UI events experienced by 53 million unique individuals, of which 1,194,819 I observe as ever having any income as a gig worker. The ever gig workers make up only about 2% of the UI recipients; however, this includes many individuals for whom gig platforms were not available.

The data do not allow me to differentiate between two separate unemployment shocks and subsequent UI claims that occur in consecutive years from benefits from one UI claim that span two calendar years. Thus, I define an unemployment event as a year in which an individual has positive unemployment compensation in a given year (as reported on Form 1099-G) and zero unemployment compensation in the prior year. I restrict to unemployment events that occur between 2008-2015 in order to have at least three pre- and post-UI event years for each individual. This drops 14 million individuals from the sample, retaining 39 million unique individuals who experience 49 million UI events. For the 23% of individuals with multiple events, I select the first event within this time period.

Finally, I restrict the sample to UI recipients living in counties where gig platforms eventually enter during the time period of analyzed UI events (2008-2015). This excludes counties where gig platforms never enter or where the first gig platforms had not yet entered as of 2015.[43] Appendix Figure A4 identifies the 819 selected counties out of 3,021 US counties. As seen in Appendix Figure A5, the selected counties contain the majority of UI claims. This sample restriction retains about 83% of all UI recipients.

[43] I infer the availability of gig platforms based on individual level data stemming from the universe of individuals in a county. See Appendix Section 2.2 for more information.

Table B1: Sample Restrictions: Numbers of Observations

	Sample			Gig Workers
	All Ages	Prime-Age	Near-Elderly	(All Ages)
All UI Events 2005-2017				
Number of UI Events	68,510,061	91,340,712	17,877,935	1,623,961
Unique Individuals	53,073,619	38,827,643	8,277,077	1,194,819
...with 1 UI event	40,087,646	27,446,153	7,087,937	839,646
...with 2+ UI events	12,985,973	11,381,490	1,189,140	355,173
Restricting to First UI Event 2008-2015				
Number of UI Events	48,644,065	36,713,725	7,052,173	1,176,865
Unique Individuals	38,714,964	28,003,976	6,161,833	886,164
Unique Individuals (sample restrictions)				
First UI Event 2008-2015	38,714,964	28,003,976	6,161,833	886,164
Drop non-US counties	38,714,964	27,965,010	6,157,708	885,451
Drop never Gig Areas	34,956,717	25,343,612	5,565,168	875,217
Drop gig after 2015 areas	32,217,165	23,375,773	5,131,582	863,565
Final Stratified random sample				
Unique Individuals	1,177,101	917,128	106,243	863,565

Notes: This table provides population weighted counts for the overall sample and the two sub-groups focused on in this paper. Prime-age workers are ages 25-54 at UI receipt. Older workers are those ages 55-69 at the time of UI receipt. Each row denotes the number of observations or unique individuals in each sample restriction.

Appendix C Take-up of Unemployment Insurance

The purpose of this section is to test if the rollout of gig platforms affected the take-up rate of UI benefits. Using publicly available data from the Department of Labor Employment and Training Administration on the number of unemployed and insured unemployed at the state-quarter level, I estimate the following regression equation:

$$\begin{aligned} InsuredUnemployed_{st} =& \alpha + \beta_1 TotalUnemployed_{st} * GigUnavailable_{st} \\ &+ \beta_2 TotalUnemployed_{st} * GigAvailable_{st} + \eta_s + \gamma_t + \varepsilon_{st} \end{aligned} \quad (4)$$

I aggregate the county-level availability, described in Section 2.2, to the state-level by taking the earliest year of gig availability year across all counties in a state. Since this is a much noisier approximation of gig availability across counties within a state, I simply present the coefficient as a pre- versus post-gig availability rather than approximating gig intensity based on the number of years. Figure C1 presents the regression coefficients visually. Accounting for year and state fixed effects, there was a take up rate of UI in states and years where gig platforms were available and were not of 28% and 28.6%, respectively. Estimates of β_1 and β_2 are not statistically different from one another —I present standard errors in parantheses.

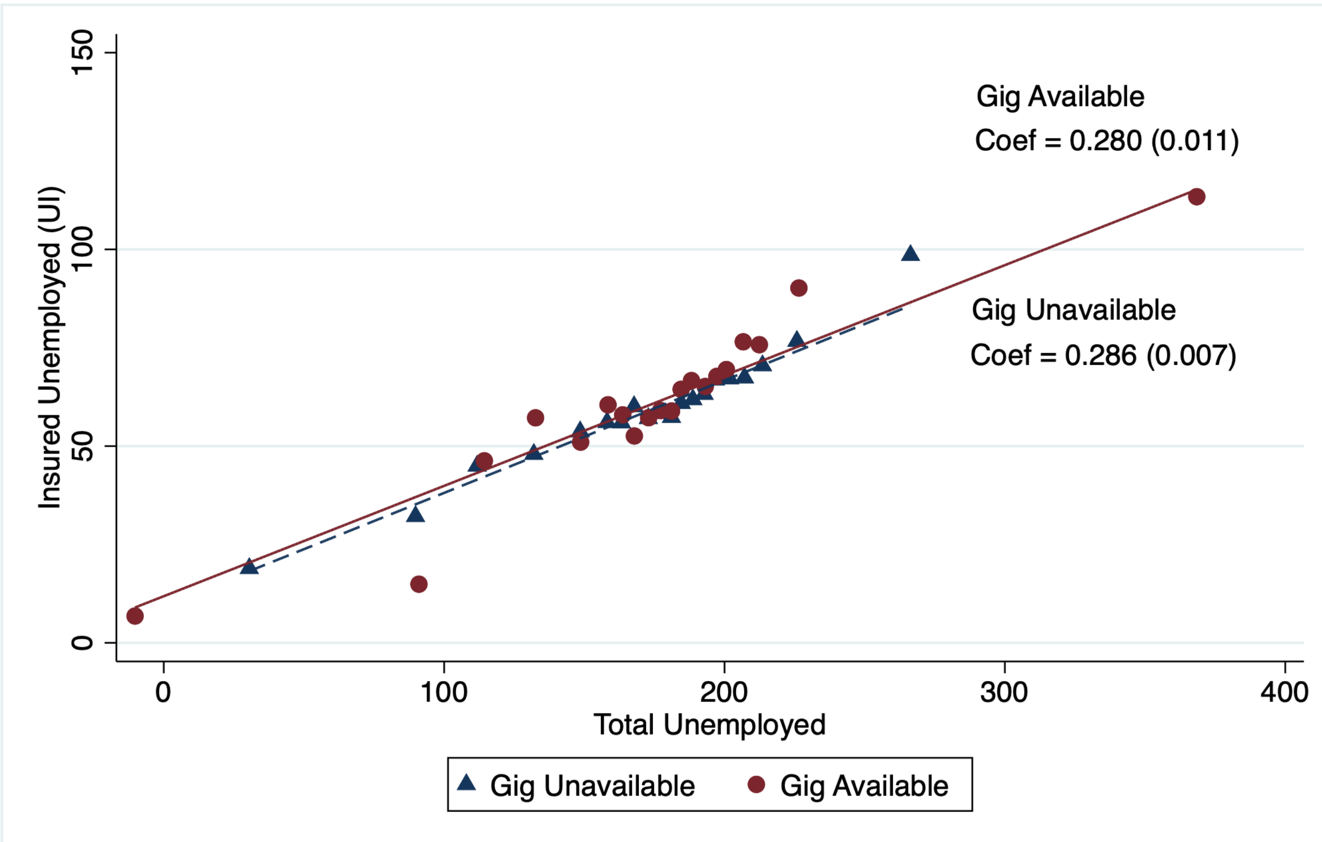
While gig availability does not appear to affect individuals decision to take up UI benefits, it may affect the duration of UI benefits and/or the amount of benefits that an individual receives. I examine this in Figure C2. While I do not find a statistically significant decrease in the total amount of annual unemployment compensation that individuals receive, there is suggestive evidence that those with gig availability have slightly lower annual receipt. This suggests that those individuals with gig availability are either staying on UI for a shorter duration or may be receiving lower benefits as earnings from temporary work reduces the amount of benefits for which an individual is eligible to receive.[44]

Tables C1 and C2 present data on the characteristics of unemployment insurance applicants and recipients from the Bureau of Labor Statistics (BLS). Table C1 provides summary characteristics on individuals by whether they apply for UI insurance to highlight differences and similarities between these two groups. Those who applied for UI in 2018 tended to be older, were more likely to be male, and were more likely to hold a professional certification or license. Table C2 provides summary statistics on potential reasons why individuals do no apply for UI benefits. The most common reason given, by 61% of respondents, was eligibility issues. The second most common

[44]The exact benefit formulas and how much income an individual can earn depends on each state's rules. Though in many states individuals may work part-time and receive reduced benefits. Therefore there is a certain threshold at which their benefits are completely offset based on their weekly earnings. Income received from contract and self-employment work is considered in addition to wages in determining how much to reduce benefits.

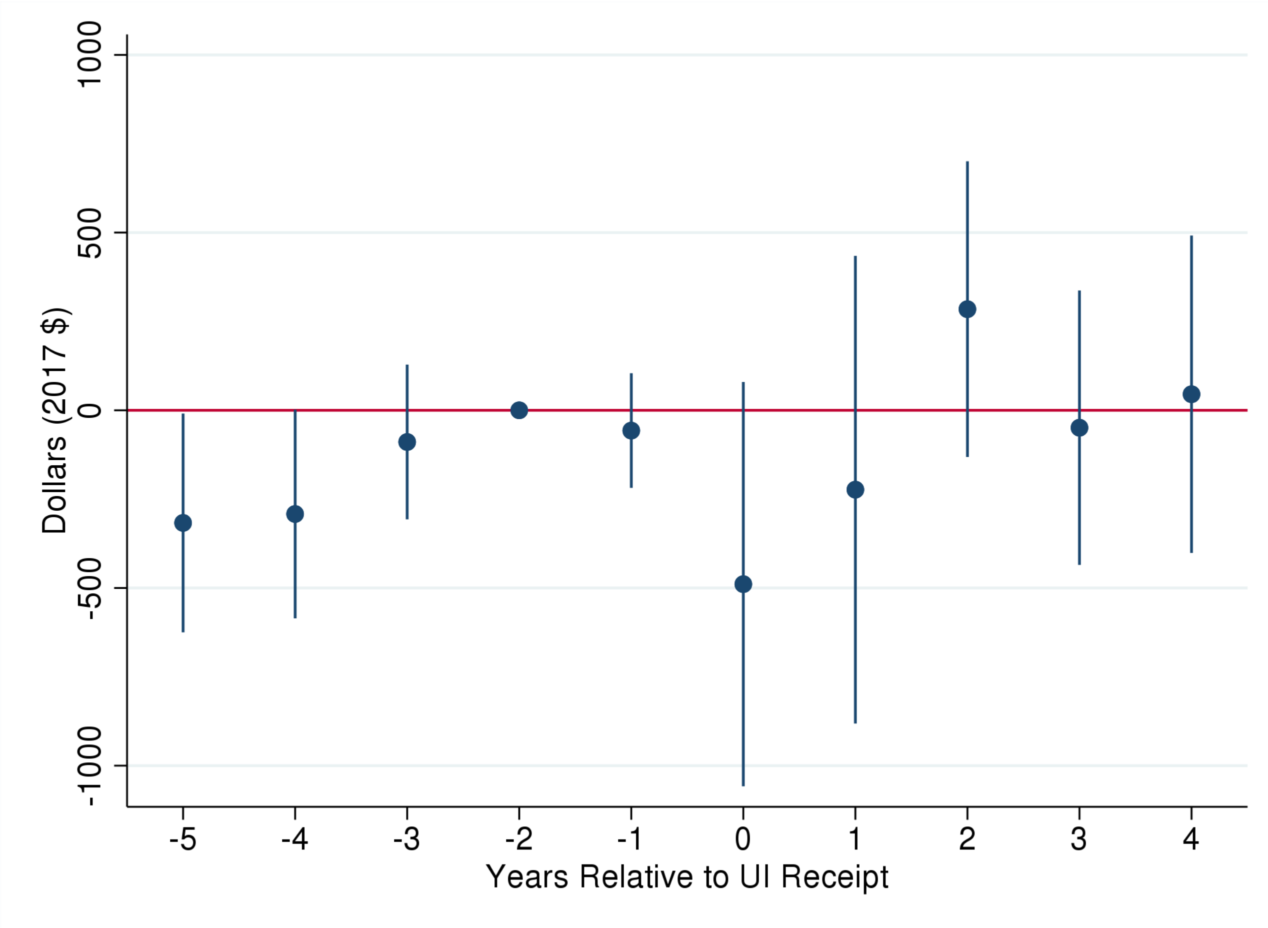
reason was the respondents expected to start working again soon.

Figure C1: Take-Up Rates of Unemployment Insurance (UI)



Notes: Data from Department of Labor Employment and Training Administration. Data are at the quarterly by state level, and include the total number of unemployed individuals and the number of insured unemployed. Plot controls for state and year FEs.

Figure C2: Effects on UI Compensation Amount - Duration Effects



Notes: Dependent variable is the amount of unemployment compensation in (2017 $) an individual received (Form 1099-G), and the top 1% of values are winsorized. Coefficient estimates for $T_{it}^k * G_i * H_i$ are plotted for each year in event time relative to event time k=-2. These estimates are interpreted as the effect of having the most gig availability at UI receipt compared to no gig availability among high-gig-propensity individuals, differencing out any changes that occur among the low-gig-propensity individuals, and each yearly coefficient is relative to two years prior to UI receipt. Sample balanced on event time $k \in [-3, 2]$. Regression includes individual FEs, county-by-year FEs, and age FEs. Data drawn around UI recipients first UI event in the period 2008-2015 and includes observations from 2005-2017. Robust standard errors clustered by individual.

Table C1: Characteristics of UI Applicants vs Non-Applicants

	Unemployed in Last 12 Months	
	Applied for UI Benefits	Did Not
Ages		
16-24	0.07	0.31
25-54	0.68	0.52
55+	0.25	0.17
Female	0.42	0.47
Race and Ethnicity		
White	0.72	0.69
Black	0.19	0.20
Asian	0.05	0.04
Hispanic	0.19	0.21
With a Disability	0.08	0.08
Foreign Born	0.16	0.14
With A Certificate or License	0.51	0.11
Educataional Attainment		
Less than HS	0.09	0.13
HS Grad, No College	0.29	0.32
Some College or Associates Degree	0.30	0.29
Bachelor's Degree or Higher	0.31	0.25

Source: Characterisitcs of Unemployment Insurance Applicants and Benefit Recipients — 2018
https://www.bls.gov/news.release/pdf/uisup.pdf

Table C2: Reasons for Not Applying for UI Benefits

Table 3. Main reason for not applying for unemployment insurance (UI) benefits among unemployed persons who had worked in the past 12 months, 2018

[Numbers in thousands]

Main reason for not applying for UI benefits	Unemployed persons[1] who did not apply for UI benefits	
	Total	Percent distribution
Total, 16 years and over	3,982	100.0
Eligibility issues	2,425	60.9
Job separation type (quit, misconduct, etc.) or work not covered by UI	1,261	31.7
Insufficient past work	734	18.4
Previous exhaustion of benefits	66	1.7
Any other reason concerning eligibility	364	9.1
Attitude about or barrier to applying for UI benefits	476	12.0
Do not need the money or do not want the hassle	267	6.7
Negative attitude about UI	56	1.4
Do not know about UI or do not know how to apply	120	3.0
Problems with application process	33	0.8
Other reasons for not applying for UI benefits	886	22.3
Expect to start working soon	404	10.1
Did not apply for personal reasons	154	3.9
Plan to file soon	100	2.5
All other reasons	228	5.7
Reason not provided	194	4.9

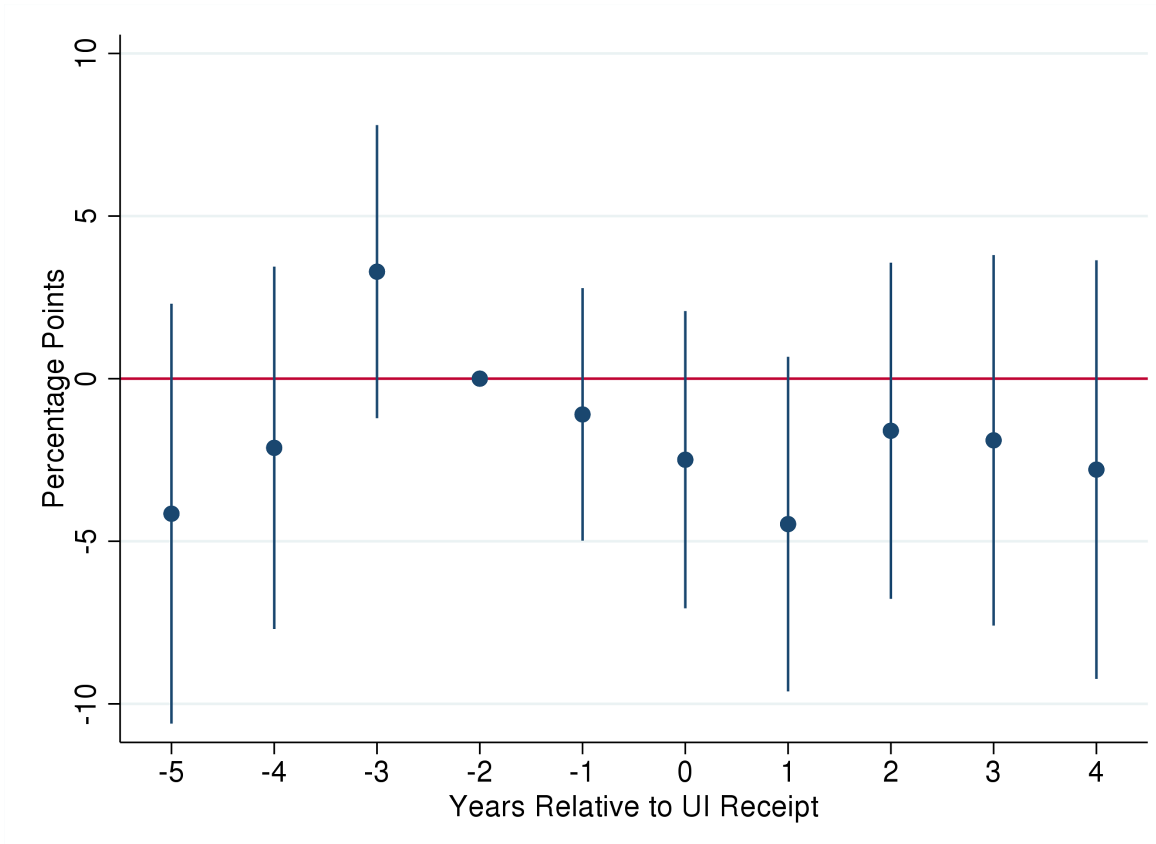
[1] Data exclude unemployed persons with no previous work experience and those who last worked more than 12 months prior to the survey.
NOTE: Estimates are an average of data collected in May and September 2018. Dash indicates no data or data that do not meet publication criteria (values not shown where base is less than 75,000).

Source: Characteristics of Unemployment Insurance Applicants and Benefit Recipients – 2018. https://bls.gov/news.release/pdf/uisup.pdf

Appendix D Changes in Education Decisions

In this appendix, I examine how the availability of gig platforms affects individuals decision to attend a post-secondary institution. For example, workers may forego additional education or vocational training following an unemployment shock in exchange for earning income through the gig economy. Alternatively, the flexibility that gig work provides may allow more individuals to go back to school following job loss when they might not otherwise have been able to. I estimate Equation 3 with an indicator variable for being a post-secondary student in a given year as the outcome variable, and present the results in Appendix Figure D1. At least for prime-age workers, I find no evidence of changes in education decisions among high-gig-propensity individuals with more gig availability.

Figure D1: Yearly Coefficients for Being a Student

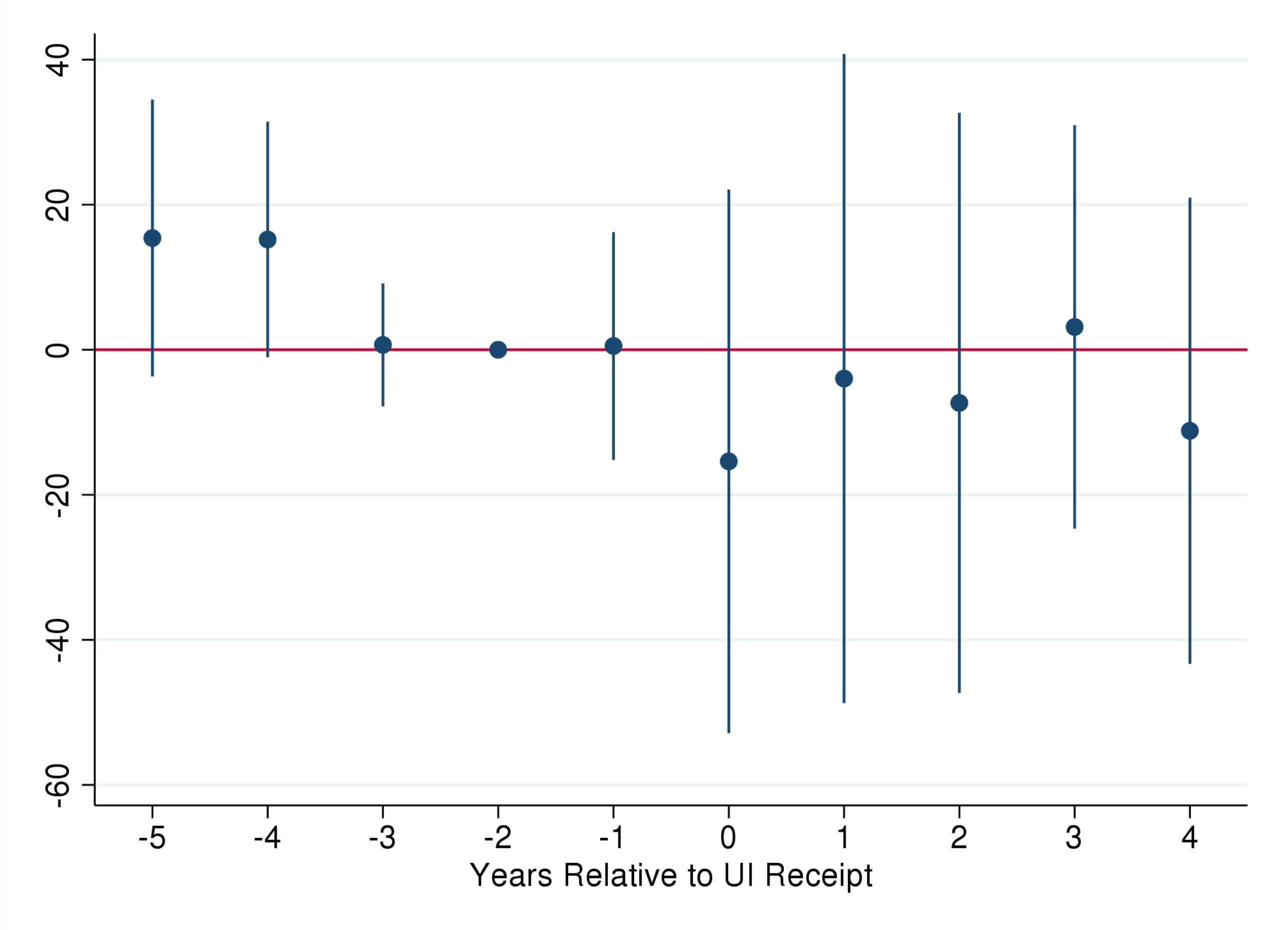


Notes: Dependent variable is an indicator for being a student in a given year as identified by having an eligible tuition payment on Form 1098-T (in percentage points 0 or 100). Coefficient estimates for $T_{it}^{k} * G_i * H_i$ are plotted for each year in event time relative to event time $k = -2$. Sample balanced on event time $k \in [-3, 2]$. Regression includes individual FEs, county-by-year FEs, and age FEs. Data drawn around UI recipients first UI event in the period 2008-2015 and includes observations from the tax years 2005-2017. Robust standard errors clustered by individual.

Appendix E Social Security Withdrawals

In this appendix, I zoom in to those ages 62-67 at the time they face their unemployment shock as these are the subset of individuals who are able to respond on this margin. I estimate a comparable set of specifications to those found in Figure 9 and in column 7 of Tables 7, 8, and A2.

Figure E1: Yearly Coefficients for Social Security Retirement Withdrawals (Ages 62-67)



Notes: Dependent variable is an indicator having received social security disability income benefits (in percentage points 0 or 100). Restricted to a subset of older workers, those ages 62-67 at UI receipt. Coefficient estimates for $T_{it}^k * G_i * H_i$ are plotted for each year in event time relative to event time k=-2. These estimates are interpreted as the effect of having the most gig availability at UI receipt compared to no gig availability among high-gig-propensity individuals, differencing out any changes that occur among the low-gig-propensity individuals, and each yearly coefficient is relative to two years prior to UI receipt. Sample balanced on event time $k \in [-3, 2]$. Regression includes individual FEs, county-by-year FEs, and age FEs. Data drawn around UI recipients first UI event in the period 2008-2015 and includes observations from 2005-2017. Robust standard errors clustered by individual.

Table E1: Results—Older Workers - Social Security Withdrawals

VARIABLES	(1)	(2)	(3)
	Has Soc Sec Ret (x 100)		
Post	9.916***	26.91***	11.65***
	(2.879)	(3.701)	(2.767)
Post x Gig Intensity	8.345	8.774	3.073
	(8.569)	(7.577)	(6.168)
Post x High	21.23**	5.393	7.634
	(9.419)	(5.325)	(6.142)
Post x Gig Intensity x High	-28.68	-12.06	-13.84
	(18.94)	(13.97)	(15.02)
Short Run (First Post Year)	X		
Long Run (Two-Four Years Post)		X	
Pooled (All Post Years)			X
Observations (Unweighted)	31,723	42,789	57,196
Observations (Weighted)	531,376	734,799	973,144
R-squared	0.791	0.877	0.807
Pre-Period Dep Var Mean	7.25	7.25	7.25
Pre-Period Dep Var SD	25.93	25.93	25.93

Notes: Results presented for a subset of older workers, those ages 62-67 at UI receipt. Post UI, $k \geq 0$, indicate years following (and including) UI receipt. Gig Intensity is a measure, between 0 and 1, of the degree of gig availability in the county in which an individual lives in at the time of unemployment insurance receipt and is fixed within individual. High is an indicator variable denoting that an individual is in the high predicted gig propensity sample. Regression includes individual fixed effects, county-by-year FEs, and age FEs. Data drawn around UI recipients first UI event in the period 2008-2015 and includes observations from tax years 2005-2017. Robust standard errors clustered by individual in parentheses ($^{***}p < 0.01,^{**}p < 0.05,^{*}p < 0.1$).