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, skill acquisition, 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+), I find an increase in gig work corresponds to a postponement of Social Security retirement benefits and a reduction in receipt of Social Security Disability Insurance (SSDI).

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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

[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.

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 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

[3]Population has an R squared value of .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.

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, 1997). 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 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 near-elderly and elderly workers (ages 55+), 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

[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.

[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, Shoven, and Slavov, 2017).

and available options following job loss for each age. As I'll show, 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 the older population, gig work prolongs labor force participation. An increase in gig work instead reduces receipt of Social Security Disabiltiy Insurance (SSDI) benefits and claiming of Social Security retirement benefits, which can be financially advantageous.

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]

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. 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. 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.[9] In fact, many drivers cite their prefer-

[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 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, Greig, and Hamoudi, 2018; Katz and Krueger, 2019), and that the percentage of workers engaged in alternative work arrangements and contract work is increasing more broadly (Jackson, Looney, and Ramnath, 2017; Collins et al., 2019; Katz and Krueger, 2019). I show in earlier work that most of the growth in self-employment appear primarily to be providing labor services as contractors or freelancers (Jackson, Looney, and Ramnath, 2017) and is largely being driven the by the growth in gig work mediated through online platforms (Collins et al., 2019).

[9] 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

ence 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.

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 workers, and near-elderly and elderly individuals. I provide evidence on robustness in Section 6. Finally, I conclude in Section 7.

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 all of the employers or payers from whom they received payments. 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

amenity or attribute (Goldin, 2014; Maestas et al., 2018; Wiswall and Zafar, 2018).

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.[10] 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 populated by 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).[11] 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.

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

[10] 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.

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

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).[12]

I am able to 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. Thus, I first describe the uses of each form and then how I identify the subset of these issued for work conducted for the online platform economy.

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.[13]

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).

Employing the same methodology as I use in my earlier paper Collins et al. (2019), I identify a list of approximately 50 large online gig platforms from publicly available lists. Appendix Table A2 lists the labor platforms I have identified with co-authors in Collins et al. (2019) and used here. For each of these 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.

[12] Information returns are sent from platforms to the IRS regardless of whether an individual ultimately files their taxes.
[13] See Appendix B.1 for additional details on Forms 1099-MISC and 1099-K.

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 x 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.[14] Appendix Figure A3 highlights the variation across counties over time in the availability of gig work as defined by this measure.

2.3 Sample Construction

I first identify the population of individuals with any positive unemployment compensation in the years 2005-2017. Of 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 they are the group of interest and make up 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 A1 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 14-82 at UI receipt, to exclude outlying or potentially erroneous observations and I also drop all individuals who die during the period three years pre- or post-UI. 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 near-elderly and elderly, ages 55 and older. 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 individu-

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

als, of which 1,254,000 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 48 million UI events. For the 25% 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.[15] Appendix Figure A1 identifies the 819 selected counties out of 3,021 US counties. As seen in Appendix Figure A2, the selected counties contain the majority of UI claims. This sample restriction retains about 83% of all UI recipients.

The final analysis sample includes the first new UI claim between 2008 and 2015 for individuals who experience this UI event in a county where gig platforms enter before 2015. 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). There are 22 million prime-age workers and 6 million near-elderly and elderly workers who experience an UI event in my final analysis sample, from which I draw my stratified random sample.

[15] 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.

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 based off their filing on the Individual Tax Return (Form 1040). Since I also observe income for non-filers, I construct a second income measure to incorporate this additional information.[16] For individual income, for filers I assign half of the household's adjusted gross income (AGI) 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). Household income on the other hand I have to restrict to the subsample of filers as I cannot identify an individual's spouse in years when they do not file, and I simply use AGI as reported on Form 1040. 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.

[16] 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.

For each, I evaluate both the extensive margin, measured as a dummy variable for any level of employment of 0 versus 100 (to be in percentage point terms), 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 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 provide this form to all students and the IRS identifying 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%. 46% of the sample is female and on average individuals are 36 years old. Among the 91% who filed, household AGI is on average $54,154 and the median household income is $38,100.[17] Individual income is on average $37,963 and almost entirely attributable to wages which are on average $38,130.[18] Additionally, the individual is typically the primary wage earner within the household, as spouses' wages are on average $14,152 relative to the individual's wages, $38,130.

[17] 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.

[18] 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.

On average over the three years prior to unemployment, 92% held a wage job. This is high by construction, as to receive UI the individual must have first held a wage job from which to become unemployed. Additionally, 14% 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.[19] On the other hand, the median household AGI among this sample, $29,500, is substantially lower. As a result, a slightly higher number of these individuals, 23%, live in households that claimed the EITC.

3 Descriptive Evidence on Behavior around UI Receipt

Figures 2 and 3 illustrates 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 for magnitudes in subsequent analyses. I describe prime-age workers in Figure 2 and near-elderly and elderly workers in Figure 3.

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.[20] Even by

[19] 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).

[20] 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 live in an area with gig availability prior to the year of UI receipt; for this reason, these means are not necessarily . However, we see that even if this is occurring, individuals

four years after job loss, only 0.4% of individuals have any gig work. To put this is context, this is about five times smaller than those who had gig platforms available of whom 2% had any gig work.

Household AGI increase on average from $42,000 to $50,000 prior to job loss. In the year of UI receipt and the following year, households lose about $5,000, a drop on average from $50,000 to $45,000. Similarly, individual income drops from about $35,000 to $29,000.

Annual wage earnings conceals 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 of interest. This increase 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 drop of 17 percentage points. Two years following UI receipt we see an increase of about 5 percentage points in holding a wage job, indicating that roughly one-third of individuals are able to return to the work force. This does not appear to increase over time following the initial increase

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

The spouse of an 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. Following job loss, we observe a clear spousal labor response given a shift in slope of zero to a positive slope of wage earnings. Indicating that, on average, an individual's spouse is contributing more to the household income following the unemployment shock.

appear to have essentially no gig work prior to job loss.

In terms of post-secondary education, on average about 19% of the individuals are enrolled with eligible tuition payments five years prior to job loss. This is trending downward leading up to job loss, as these 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 points in schooling in the two years surrounding job loss, before continuing to decrease on the same trend as prior to job loss.

Near-Elderly and Elderly

In Figure 3, there are some key differences in the patterns that the near-elderly and elderly 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 percent of individuals holding a subsequent wage job following job loss of almost 30 percentage points. Additionally, there is not a small increase the year following UI receipt after individuals find jobs. 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 benefits; though this is trending up more prior to job loss and so does not exhibit as pronounced of an increase following job loss.

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 there is selection and not random take up of 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 of gig. 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 a 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 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 with describe both of these sources variations in significantly more detail.

4.1 Variation in Gig Availability

I leverage variation in the date at which gig firms enter different cities 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. For example, Uber entered San Francisco in 2010, New

York in 2011, and Los Angeles in 2012.[21] Thus, 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 Uber had not yet entered.[22] A simple difference-in-difference exploiting the rollout variation assumes that the timing of gig firms entry into a city is orthogonal to worker labor supply decisions.

Figure 4 illustrates the geographical variation in gig availability and prevalence across counties in 2013 and 2016.[23] 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, where as 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 58% 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 5 shows

[21] These examples are for illustration purposes only and based off publicly available entry data of the Uber platform. https://www.uber.com/newsroom/

[22] Several other papers have exploited variation driven by the launch of various gig platforms, most commonly Uber, across cities (Brazil and Kirk, 2016; Dills and Mulholland, 2017; Berger, Chen, and Frey, 2018; Hall, Palsson, and Price, 2018; Koustas, 2018; Buchak, 2019). Additionally, Mishel (2018) estimates that Uber makes up approximately two-thirds of the gig economy, and thus these studies should be using similar rollout dates.

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

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 rollout 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 A4 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 growth in gig prevalence following the entry of platforms into a county.

I consider the "treatment" of gig availability that each individual receives 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 $\frac{1}{3}$.

Figure 6 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 Figure 6 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 for those filing jointly, the share of the household earnings that the individual contributes. Third, I include filing status, marital status and number of

claimed children living in the household.[24] 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.[25] 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 two groups: high gig propensity, the top 1% of the sample, and low gig propensity. 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. 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 A6a. Additionally, I drop the bottom half among the low gig propensity individuals so that the low gig propensity individuals I compare with are more comparable to the high gig propensity individuals. Appendix Figure A6b 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 for the subsample of high gig propensity individuals. Relative to the overall sample of UI recipients, these individuals are less likely to be female (30% versus 37% female), slightly younger (33 versus 35), and less likely to be married (27% versus 30%). On average, they have a lower household AGI, $34,849, and individual income, $26,135. They're about twice as likely to have held a gig work position in the pre-UI years, 0.58% vs 0.30%.

Figure A5 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 a few of the key predictive variables. Figure A5a demonstrates that younger individuals are more likely to work in the gig economy. This measure peaks around age 25 and those below 25 have slightly lower propensities on average. Figure A5b and Figure A5c show that

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

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

those with lower incomes and wages two years prior to UI receipt are more likely to participate in gig work. Figure A5d shows that individuals whose wages make up a larger share of the households 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 (1997). 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, and single year of age fixed effects.

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.

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

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 es-

timated 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 measure of gig work to quantify to what extent individuals start working in the gig economy after losing their job. Figure 7a shows an increase of 10.45 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 20.45 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 7a 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 expected 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 7b, I present the corresponding results with an intensive margin measure of gig work —gig earnings (in 2017 dollars).[26] The 10.45 percentage points increase in gig work corresponds to a roughly $609 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 $1,926, implying each annual average gig earnings of roughly $7,900. Implied average annual gig earnings for those with 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.[27]

As one of my key objectives in this paper is to disentangle short and long run labor supply

[26]Dollars are adjusted using CPI-U from BLS: https://www.bls.gov/cpi/home.htm.
[27]$15,000 is roughly 2,000 hours at the federal minimum wage, $7.25. (https://www.dol.gov/whd/minimumwage.htm)

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 $k = 0$ as the post period of interest while the long run estimates present $k \in [2, 4]$ as the post period of interest.

In Table 4, I show that in the year of UI receipt gig work increases on the extensive margin by 10.83 percentage points and $639.2 in gig earnings, for high gig propensity individuals relative to those without gig platforms available. Only 0.01 percent of the individuals had any gig work in the pre-period. As seen in Table 5, by two to four years after UI receipt the increase in gig work is 21.09 percentage points and $2,960 in gig earnings. For completeness, I also present coefficients where I pool the short and long run effects for all outcomes in Appendix Table A3.

Individual and Household Income

Given the increase in gig work, to what extent does this recover lost income with job loss? Figure 8 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 $2,913 less. As illustrated in Figure 8, 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 of long run post years. The coefficient -$2,247 indicates that high gig propensity individuals with

the maximum gig availability at the time of UI receipt is $2,247 lower two to four years follow UI receipt than comparable individuals who did not have any gig availability.

Appendix Figure A7 exhibits an analogous pattern for household income. Column 4 of Table 5 suggests a larger decrease of about $4,026 when accounting for household income rather than 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

I show that this reversal in income recovery is explained by lower wages earnings, Figure 9a, which is partly a function of the extensive margin —holding a traditional wage job, Figure 9b. 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 $4,037 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.

Recall in Figure 7a that individuals entered into gig work and stayed in these positions even a few years later. This does not necessarily exclude 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, on average they were earning roughly $14,000 and 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. 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 Near-Elderly and Elderly

Now I turn to the near-elderly and elderly individuals, those individuals ages 55 and older 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 flexible nature of gig work as a bridge to retirement (Ramnath, Shoven, and Slavov, 2017).[28]

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 near-elderly and elderly population. I present summary statistics for this older age group in Table 6. Among this sub-population (55+), approximately 80% are under age 65. The average individual is 60 years old (and the median individual is 61 years old).

Gig Employment and Earnings

Compared to prime-age workers, older workers exhibit a similar increase in gig work following job loss, Figure 10a. Figure 10a indicate 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 14.9 and 29.45 percentage points in the year of and year following UI receipt, respectively. This corresponds to an increase of $1,162 and $4,258 in gig earnings, Figure 10b.

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 be-

[28] While Ramnath, Shoven, and Slavov (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.

yond 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 15.41 percentage points ($1,145) and 33.15 percentage points ($6,415) in the short-run and long-run, respectively. These estimates imply that each gig worker is earning on average $7,400 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, Appendix Figure A8. If anything, the point estimates in Appendix Table A4 suggest that individuals with the maximum gig availability maintain the relative increase of about $4,697 in individual income and $5,557 in household AGI, though 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 x time) relative to comparable individuals 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 11 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 A4 shows this is a significant reduction of 5.7 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 12 suggests a similar drop in withdrawing Social Security retirement benefits. 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. There is a 2.3 percentage points reduction in the short run and 4.5 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.

Since only a sub-group of the near-elderly and elderly 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 18 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.

6 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 A9, 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 A9a, 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 A9b 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 A10, 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 Appendix Figure 8. Thus, I find this

reassuring that the results I find are not driven by differential trends post-unemployment across the different groups.

7 Conclusion

In summary, I document an increase in gig work after job loss, as I identify using UI receipt. My 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+), 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 the elderly and near-elderly population.

These issues are 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, Looney, and Ramnath, 2017). Hence, changes in the employer-employee re-

lationship 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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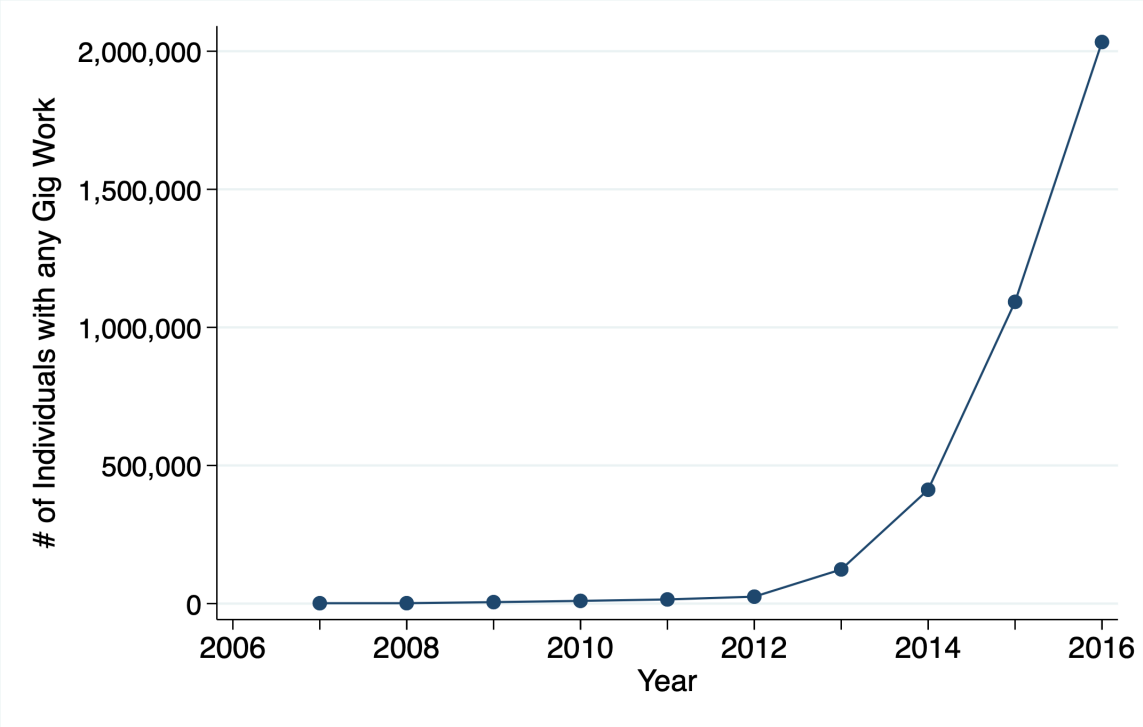
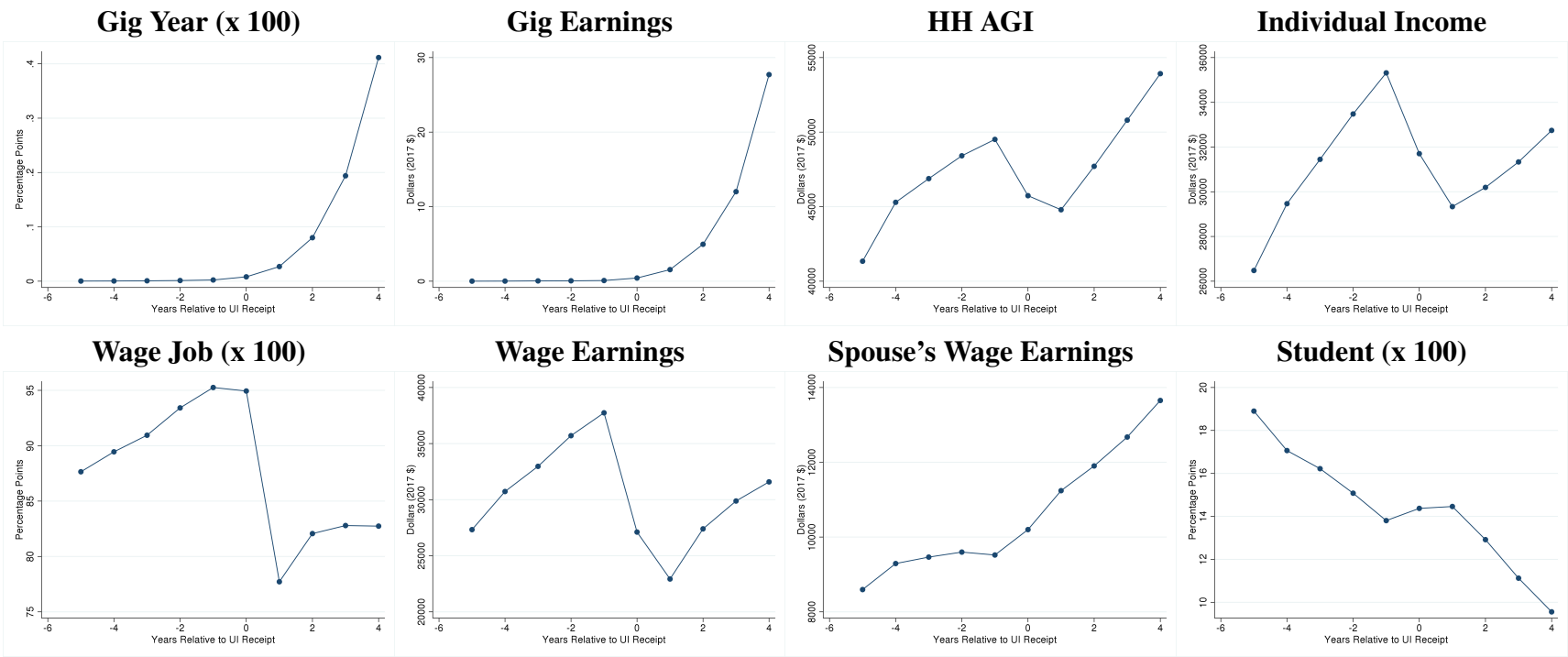
Figures and Tables

Figure 1: Number of Gig Workers by Year



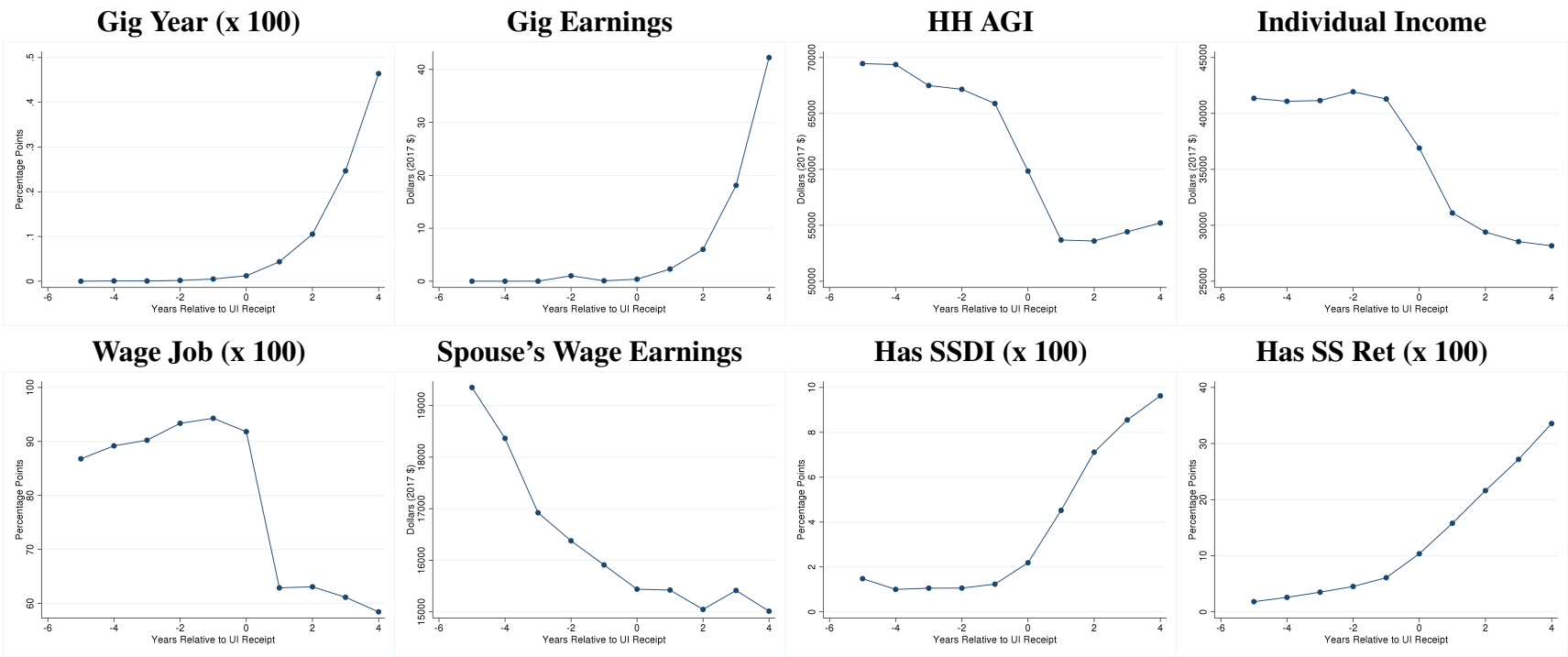
Notes: This figure presents the yearly number of individuals with any gig work as identified using the universe of federal individual income tax returns for the US. This includes counts of the universe of individuals who received Form 1099-MISC or Form 1099-K from a gig platform identified in Table A2 or filed Schedule C denoting income from one of these platforms.

Figure 2: 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 year 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).

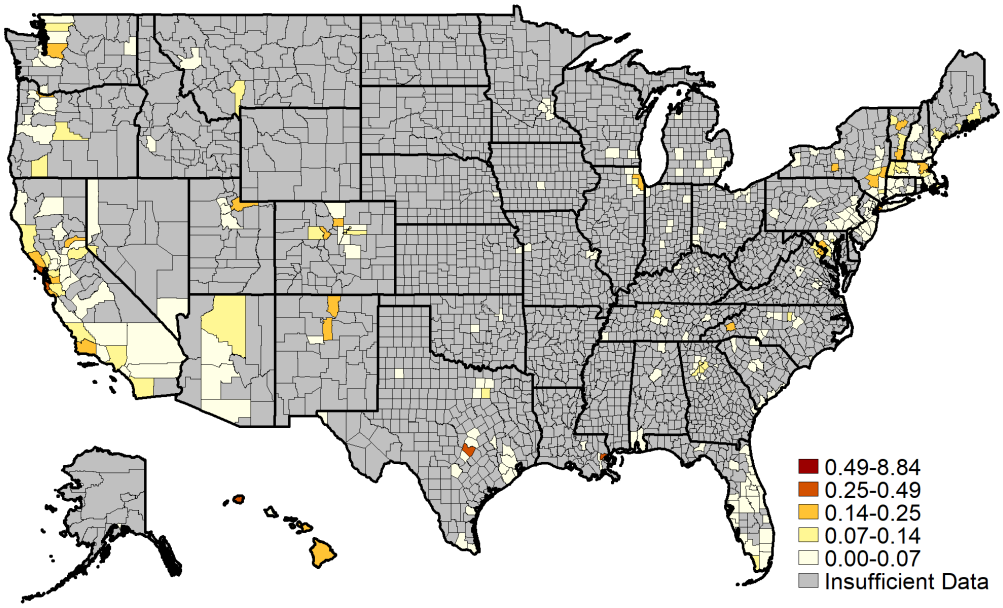
Figure 3: Summary of Key Outcome Variables by Year Relative to UI Receipt
(Near-Elderly and Elderly)



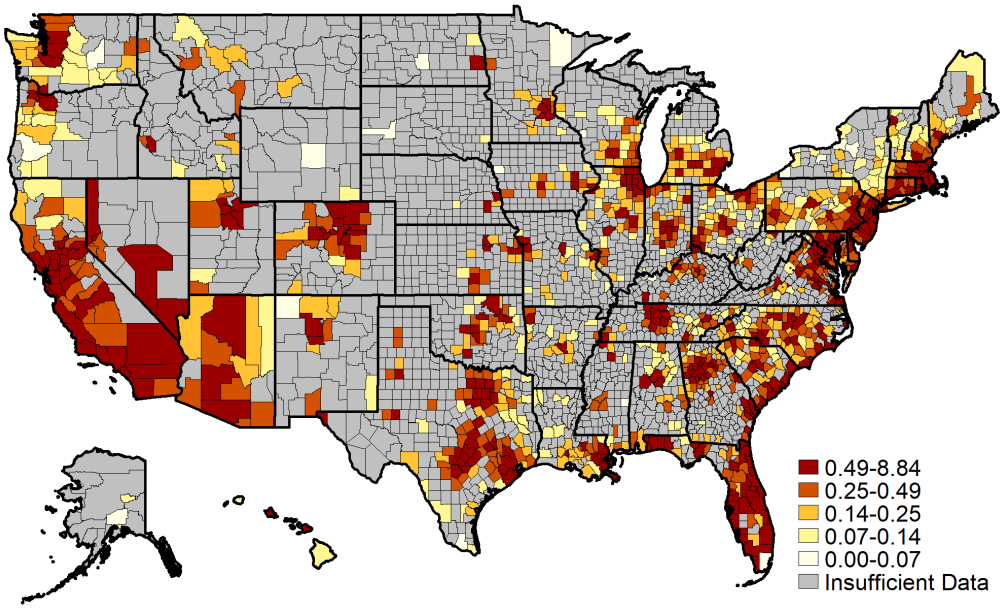
Notes: Averages of each outcome are plotted by year relative to UI receipt for individuals who become unemployed in a county and year where there are no gig platforms available. Gig year denotes having any income from gig work in that tax year. Gig Earnings are the sum of all earnings earned in the gig 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 4: Percent of a County's Working Age Population (15-64) Partaking in Gig Work

(a) Variation in 2013

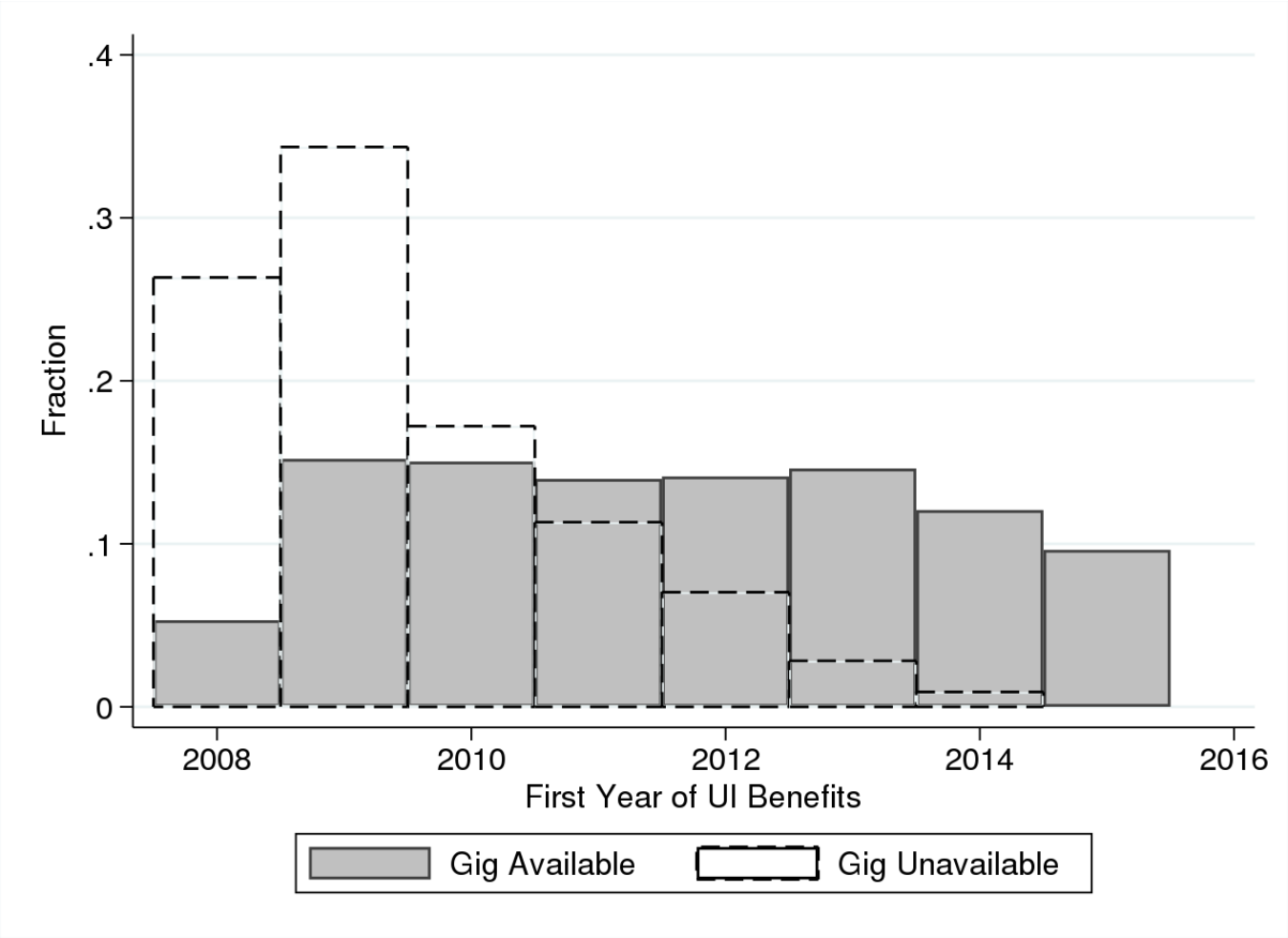


(b) Variation in 2016



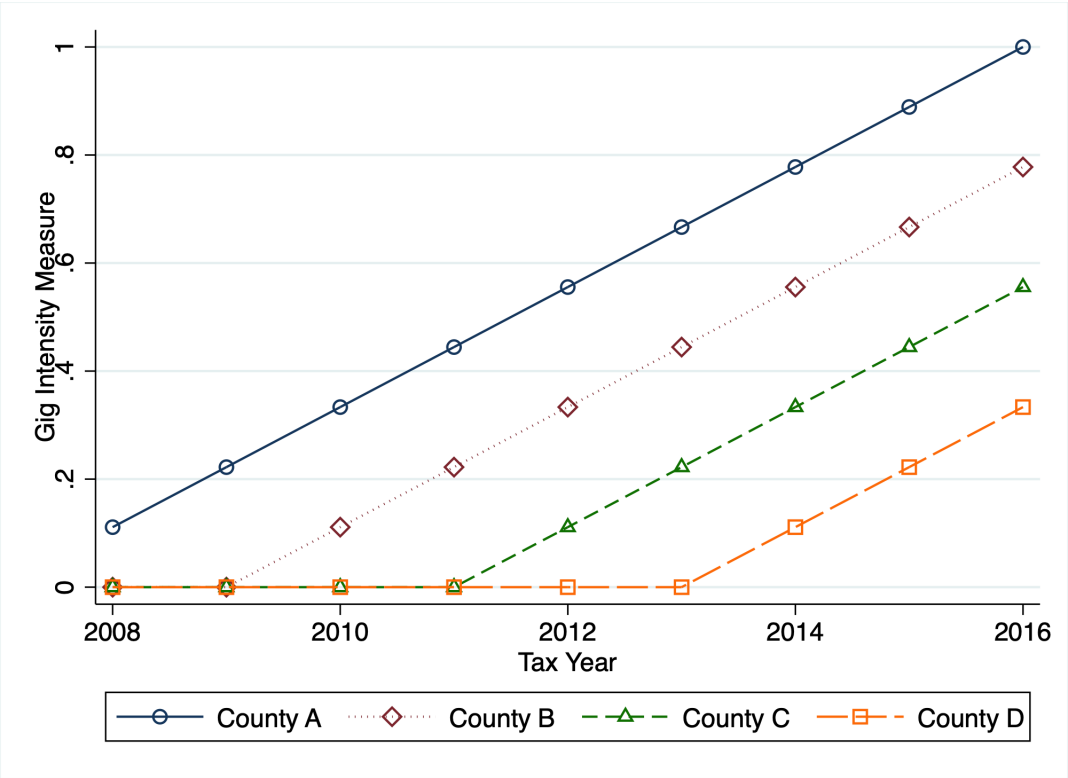
Notes: Figure 4a and 4b illustrate the geographic variation in gig platform availability at a given point in time across counties. Second, they illustrate variation within a county over time in the prevalence of gig work, as measured in the percent of the counties working age population with any amount 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 5: 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 45% of the sample had gig platforms available at UI receipt.

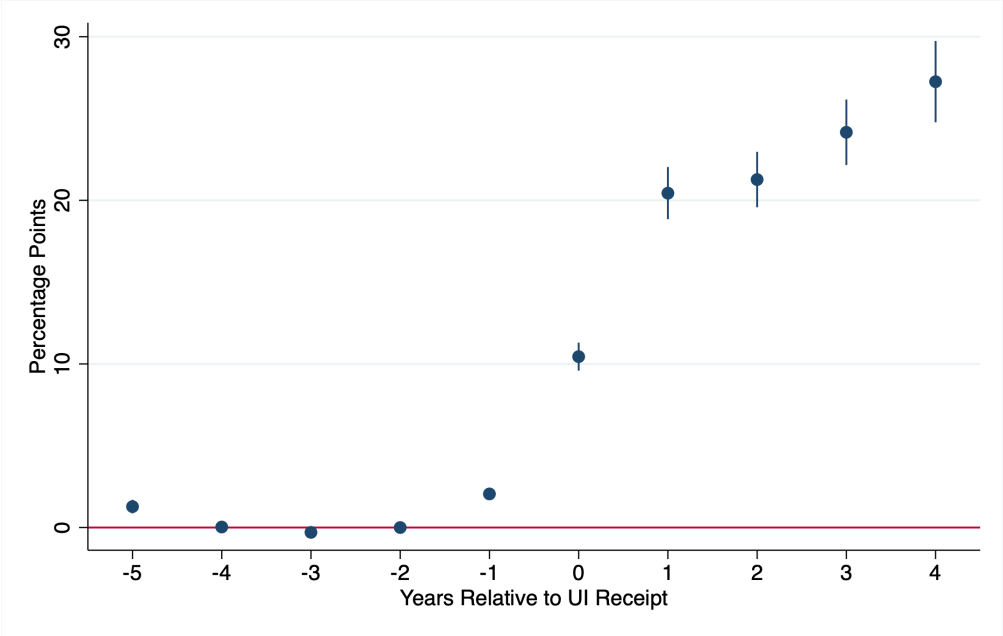
Figure 6: Illustration of Gig Treatment Intensity Variable



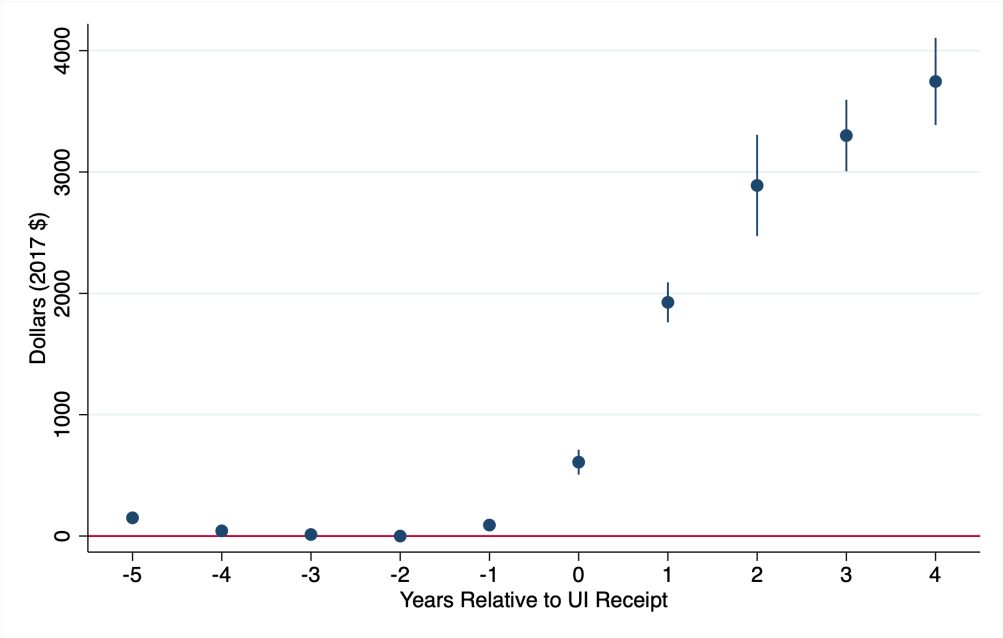
Notes: My 'Gig Intensity Measure' captures the number of years gig platforms were available in a given county in each year and is scaled by $\frac{1}{9}$ —the maximum of years gig platforms were available at the time of job loss across all individuals in my analysis —to be a measure $\in [0, 1]$. In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

Figure 7: Yearly Coefficients for Gig Work
(Prime-Age Workers)

(a) Gig Work (x 100)

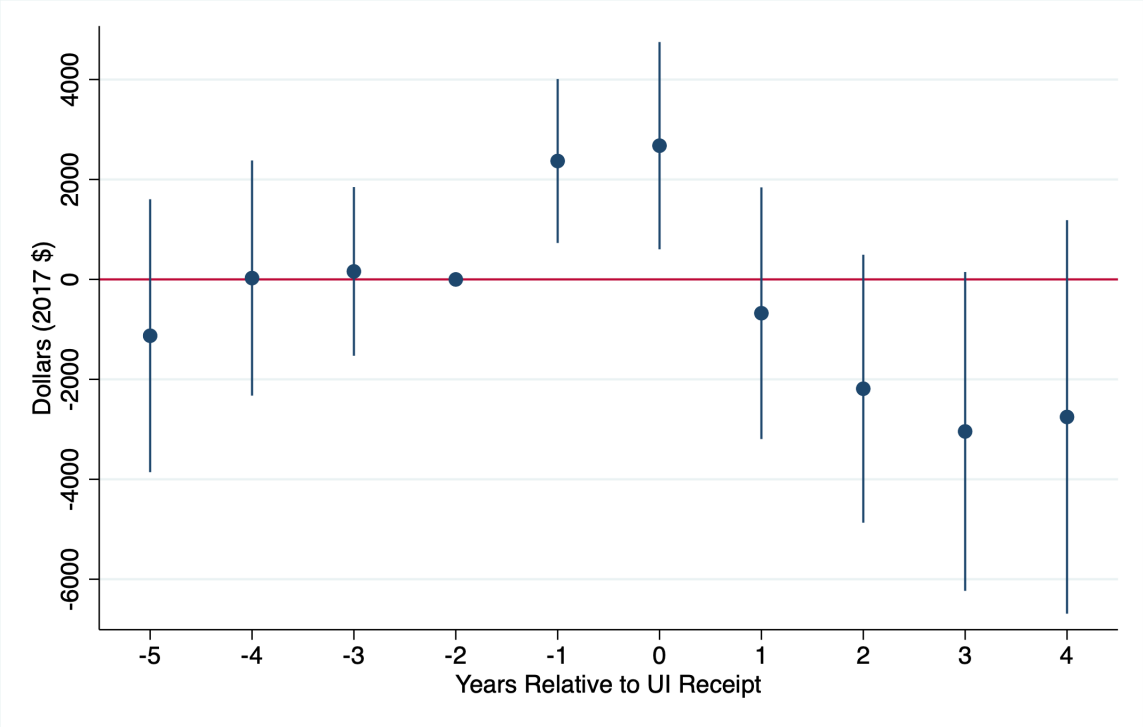


(b) Gig Earnings (2017)



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. Sample balanced on event time $k \in [-3, 2]$. Regression includes individual FEs, county x 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.

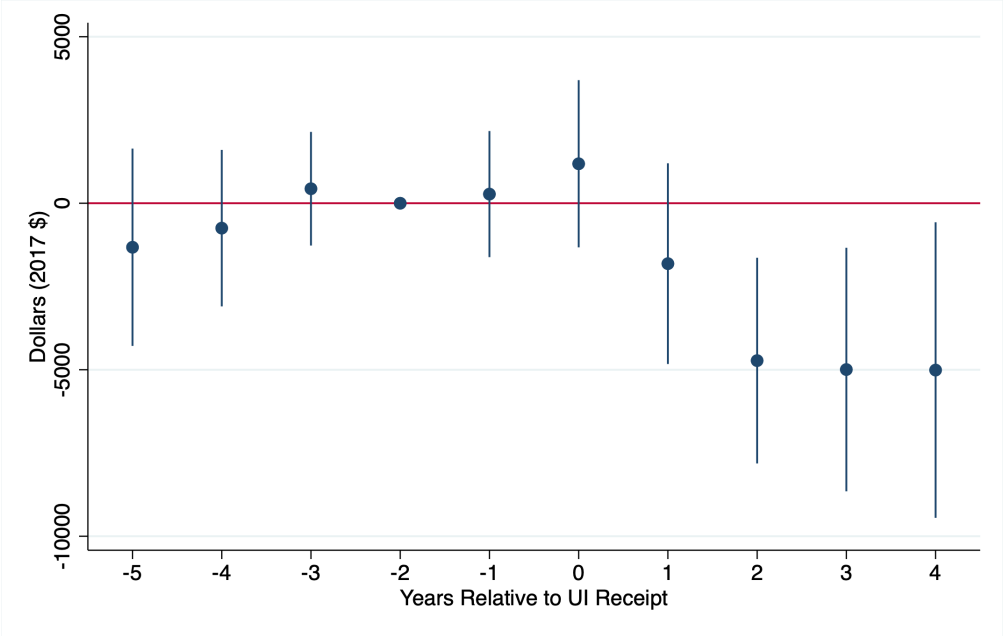
Figure 8: Yearly Coefficients for Individual Income
(Prime-Age Workers)



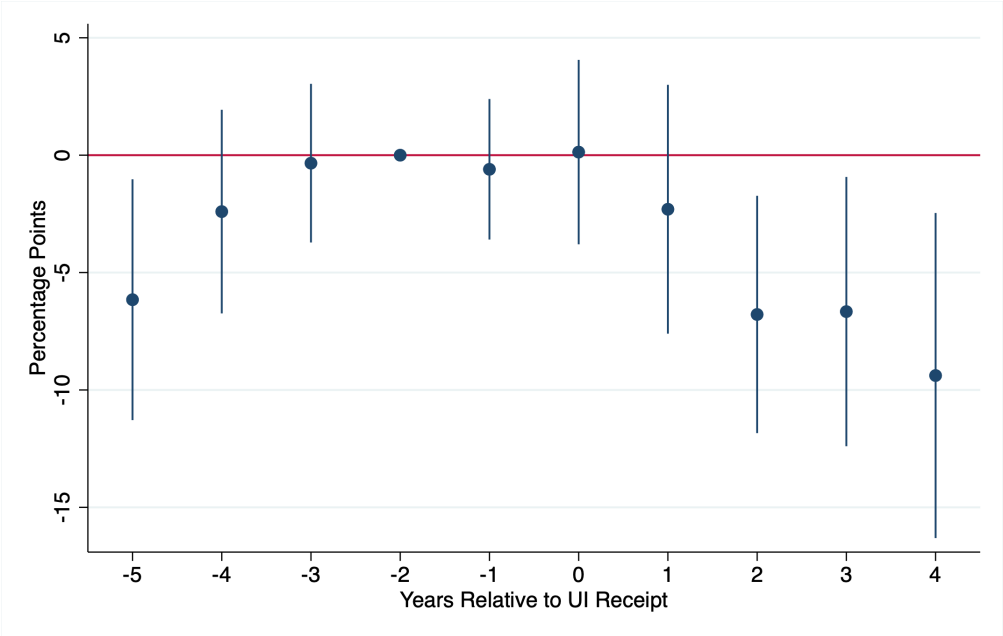
Notes: Dependent variable is individual income (2017 $), and the top and bottom 1% of values are winsorized. Coefficient estimates for $T_{it}^{k} * G_i * H_i$ are plotted for each year in event time relative to event time k=-2. These estimates are interpreted as the effect of having the most gig availability 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. Sample balanced on event time $k \in [-3, 2]$. Regression includes individual FEs, county x 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 Wage Employment
(Prime-Age Workers)

(a) Wage Earnings (2017 $)



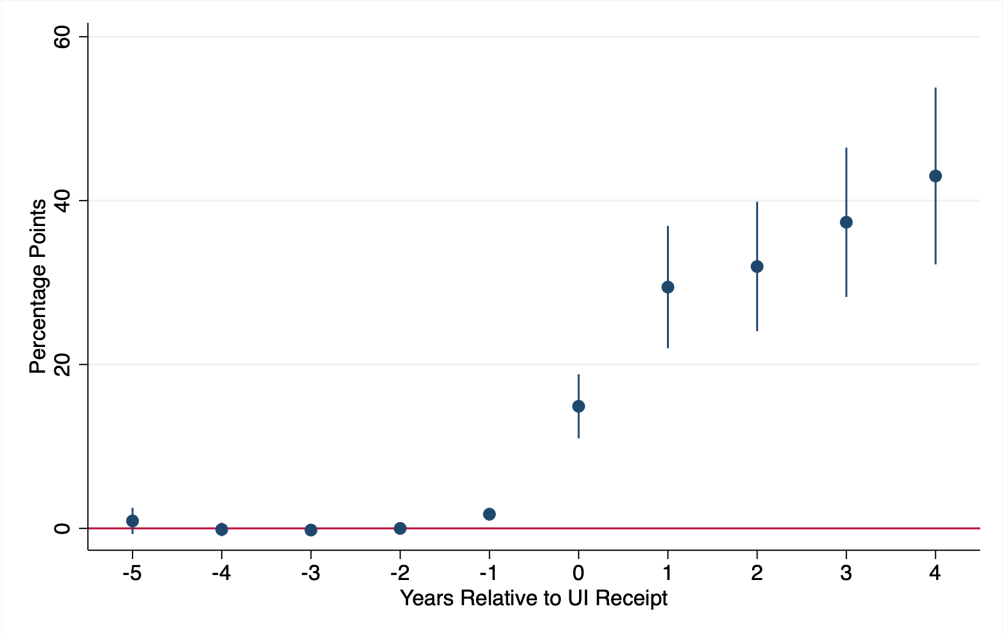
(b) Wage Job (x 100)



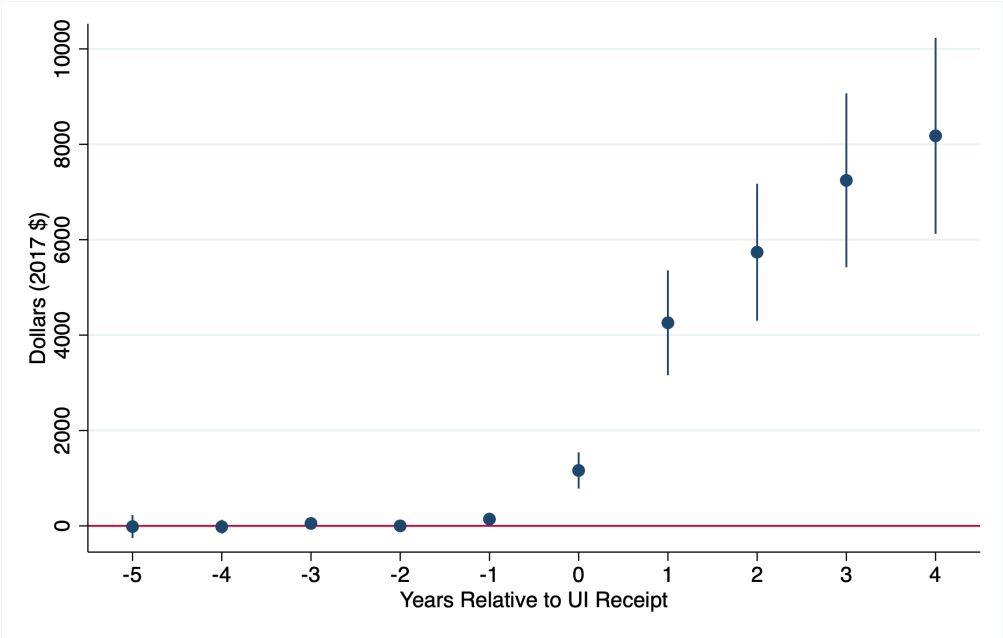
Notes: Dependent variable in the top panel is wage earnings (2017 $), and the top 1% of values are winsorized. Dependent variable in the bottom panel is an indicator for wage job (in percentage points 0 or 100). Coefficient estimates for $T_{it}^{k} * G_i * H_i$ are plotted for each year in event time 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. Sample balanced on event time $k \in [-3, 2]$. Regression includes individual FEs, county x 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 10: Yearly Coefficients for Gig Work
(Near-Elderly and Elderly)

(a) Gig Work (x 100)

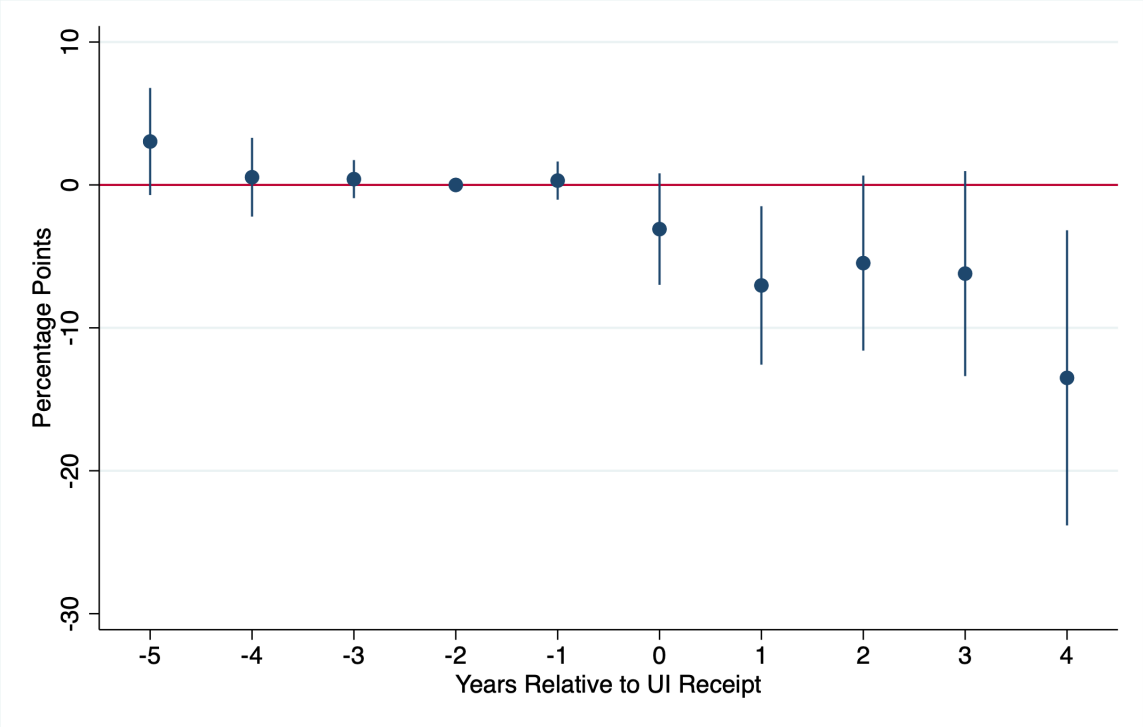


(b) Gig Earnings (2017)



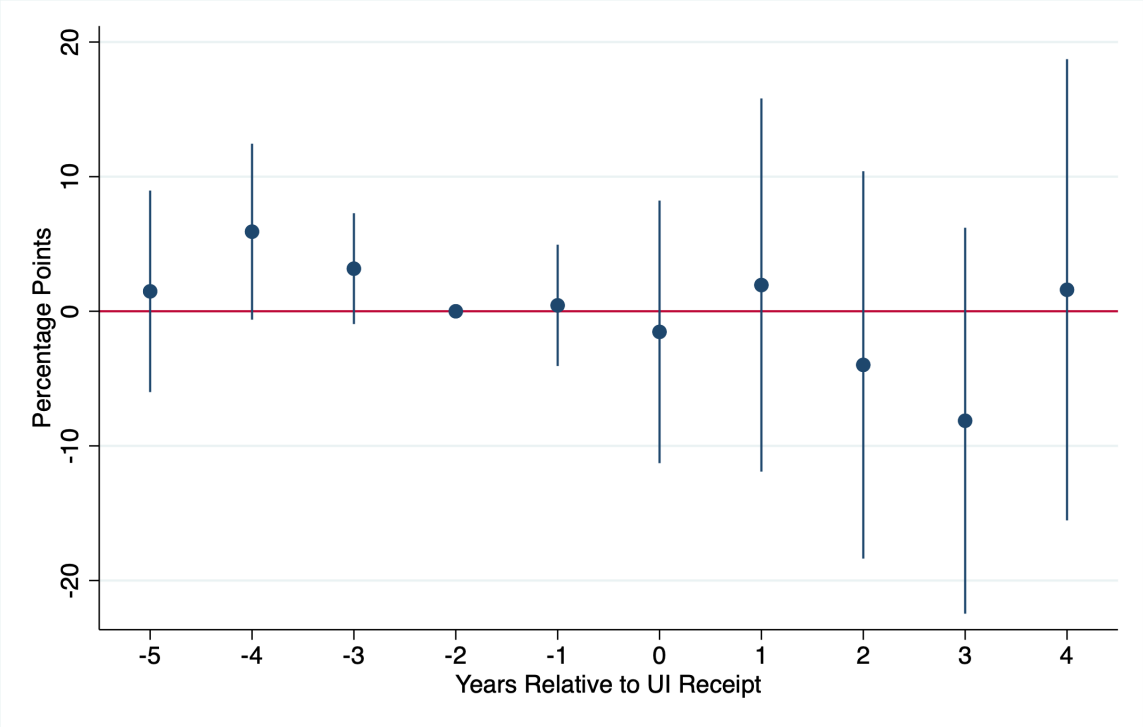
Notes: Dependent variable in the top panel is an indicator for participating in gig work, expressed in percentage points (taking the values 0 or 100). Dependent variable in the bottom panel is Gig Earnings (in 2017 $). Restricted to near-elderly and elderly sample, ages 55 and above. Coefficient estimates 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. Sample balanced on event time $k \in [-3, 2]$. Regression includes individual FEs, county x 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 11: Yearly Coefficients for Social Security Disability Insurance
(Near-Elderly and Elderly)



Notes: Dependent variable is an indicator having received SSDI benefits (in percentage points 0 or 100). Restricted to near-elderly and elderly sample, ages 55 and above. 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. Sample balanced on event time $k \in [-3, 2]$. Regression includes individual FEs, county x 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 12: Yearly Coefficients for Social Security Retirement Benefits
(Near-Elderly and Elderly)



Notes: Dependent variable is an indicator having claimed Social Security Retirement benefits (in percentage points 0 or 100). Restricted to near-elderly and elderly sample, ages 55 and above. 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. Sample balanced on event time $k \in [-3, 2]$. Regression includes individual FEs, county x 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	0.46	0.50			
Age	37	9	25	36	49
Married	0.39	0.49			
Any Children	0.45	0.50			
Household Filed	0.91	0.28			
Household AGI (2017 $)	54,154	53,958	2,400	38,100	121,400
Individual Income (2017 $)	37,963	30,534	7,200	31,600	74,400
Wage Job	0.93	0			
Wages (2017 $)	38,130	33,896	2,700	31,100	78,800
Spouse's Wages (2017 $)	14,152	28,452	0	0	54,600
Schedule C Profit/Loss (2017 $)	465	3,546	0	0	0
Schedule C (HH)	0.12	0.33			
Gig Year	0.00	0.01			
Student	0.10	0.30			
Has SSDI	0.0045	0.0669			
Has SS Income	0.0015	0.0386			
Claimed EITC (HH)	0.25	0.43			

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 Year 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 $)	34.13	35.82	(0.217)
Income ('000 $)	42.34	43.71	(0.194)
Married	0.294	0.254	(0.014)**
Student	0.178	0.170	(0.034)**
Wage Job	0.953	0.963	(0.837)
HH Wage Share	0.905	0.920	(0.118)
Tax Filer	0.935	0.932	(0.726)
Claimed EITC (HH)	0.256	0.264	(0.431)
Filed Sch C (HH)	0.141	0.139	(0.731)
2 Years Prior to UI Receipt:			
Wages ('000 $)	31.58	32.61	(0.241)
Income ('000 $)	39.68	40.48	(0.273)
Married	0.284	0.245	(0.098)*
Student	0.194	0.194	(0.059)*
Wage Job	0.929	0.913	(0.474)
HH Wage Share	0.903	0.917	(0.467)
Tax Filer	0.891	0.877	(0.218)
Claimed EITC (HH)	0.232	0.240	(0.397)
Filed Sch C (HH)	0.140	0.139	(0.622)
3 Years Prior to UI Receipt:			
Wages ('000 $)	28.69	29.81	(0.427)
Income ('000 $)	36.93	37.51	(0.274)
Married	0.271	0.231	(0.166)
Student	0.197	0.205	(0.063)*
Wage Job	0.893	0.863	(0.347)
HH Wage Share	0.903	0.918	(0.573)
Tax Filer	0.843	0.825	(0.885)
Claimed EITC (HH)	0.211	0.218	(0.376)
Filed Sch C (HH)	0.139	0.137	(0.337)
Observations	282,756	570,103	852,859
F-test of joint significance			1.1395

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				0.29	0.45			
Age	34	8	24	33	47	34	8	25	33	49
Married	0.29	0.45				0.30	0.46			
Any Children	0.37	0.48				0.40	0.49			
Household Filed	0.90	0.30				0.91	0.29			
Household AGI (2017 $)	39,015	40,473	0	28,500	86,800	44,857	43,311	2,400	33,600	121,700
Individual Income (2017 $)	30,257	24,682	5,000	25,600	59,300	34,689	27,218	7,200	29,500	74,600
Wage Job	0.92	0.27				0.93	0.26			
Wages (2017 $)	30,624	26,877	1,400	25,900	61,900	36,578	31,378	2,700	30,900	79,000
Spouse's Wages (2017 $)	8,350	21,475	0	0	35,100	8,289	20,669	0	0	54,800
Schedule C Profit/Loss (2017 $)	586	4128	0	0	1,100	472	3788	0	0	0
Schedule C (HH)	0.19	0.39				0.16	0.36			
Gig Year	0.002	0.048				0.00	0.01			
Student	0.16	0.37				0.10	0.30			
Has SSDI	0.004	0.062				0.0045	0.0669			
Has SS Income	0.001	0.031				0.0015	0.0386			
Claimed EITC (HH)	0.30	0.46				0.25	0.43			

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 Year 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	0.0122***	-0.0586	-4,185***	-5,152***	-11,577***	-1.477***
	(0.00299)	(0.244)	(116.6)	(178.5)	(139.0)	(0.189)
Post x Gig Intensity	-0.283***	-10.14***	-1,274***	-157.2	-1,119**	-2.608***
	(0.0243)	(2.242)	(484.5)	(741.0)	(570.6)	(0.792)
Post x High	-0.767***	-48.02***	-1,411***	-2,790***	-99.73	0.194
	(0.0649)	(6.747)	(396.7)	(626.1)	(482.1)	(0.727)
Post x Gig Intensity x High	10.83***	639.2***	2,913***	2,979*	1,591	1.551
	(0.448)	(50.49)	(1,088)	(1,669)	(1,250)	(1.912)
Observations (Unweighted)	2,805,551	2,805,551	2,805,551	2,544,603	2,805,551	2,805,551
Observations (Weighted)	42,338,132	42,338,132	42,338,132	38,573,970	42,338,132	42,338,132
R-squared	0.255	0.233	0.814	0.847	0.806	0.448
Pre-Period Dep Var Mean	0.01	0.33	32,856	46,655	34,101	92.8
Pre-Period Dep Var SD	0.78	95.57	25,749	40,249	29,630	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 and the year immediately after. 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 x 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	0.0387***	2.662	-8,132***	-8,452***	-14,605***	-15.53***
	(0.0124)	(2.040)	(174.6)	(277.3)	(204.8)	(0.290)
Post x Gig Intensity	-0.0837	-35.42***	762.2	-2.540	1,635***	6.074***
	(0.0624)	(8.537)	(524.7)	(852.4)	(602.1)	(0.762)
Post x High	1.871***	89.82***	249.3	-1,040	712.3	-0.796
	(0.134)	(21.44)	(473.0)	(799.0)	(574.8)	(0.819)
Post x Gig Intensity x High	21.09***	2,960***	-2,247	-4,026*	-4,037**	-4.454**
	(0.883)	(170.0)	(1,397)	(2,321)	(1,567)	(2.272)
Observations (Unweighted)	3,900,573	3,900,573	3,900,573	3,477,245	3,900,573	3,900,573
Observations (Weighted)	59,154,651	59,154,651	59,154,651	52,736,378	59,154,651	59,154,651
R-squared	0.277	0.266	0.724	0.775	0.709	0.410
Pre-Period Dep Var Mean	0.01	0.33	32,856	46,655	34,101	92.8
Pre-Period Dep Var SD	0.78	95.57	25,749	40,249	29,630	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 x 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
(Near-Elderly and Elderly)

	Mean	Std Dev	P10	Median	P90
Female	0.46	0.50			
Age	58.81	5.12	53	58	66
Married	0.58	0.49			
Any Children	0.22	0.41			
Household Filed	0.95	0.21			
Household AGI (2017 $)	75,105	62,653	12,600	59,500	156,800
Individual Income (2017 $)	47,812	34,706	12,100	40,700	91,700
Wage Job	0.95	0.22			
Wages (2017 $)	46,714	38,952	7,400	37,400	97,100
Spouse's Wages (2017 $)	16,944	29,988	0	0	60,100
Schedule C Profit/Loss (2017 $)	492	3,922	0	0	0
Schedule C (HH)	0.14	0.35			
Gig Year	0.00	0.01			
Student	0.02	0.13			
Has SSDI	0.01	0.09			
Has SS Income	0.13	0.34			
Claimed EITC (HH)	0.10	0.30			

Notes: Sample is restricted to the subsample of near-elderly and elderly workers, those ages 55 and above 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 Year 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 7: Short Run Effects on Labor Supply, Income, and Social Insurance Receipt
(Near-Elderly and Elderly)

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	0.0551***	5.374***	-4,430***	-5,037***	-4.306***	1.295***	1.659***
	(0.0153)	(2.025)	(562.2)	(884.2)	(0.939)	(0.285)	(0.471)
Post x Gig Intensity	-0.409***	-31.93***	408.0	1,153	-0.663	-0.237	1.782
	(0.0829)	(8.587)	(1,835)	(2,882)	(3.283)	(0.935)	(1.773)
Post x High	-1.304***	-102.4***	-2,162	-4,131*	0.397	0.221	2.558
	(0.303)	(28.49)	(1,592)	(2,368)	(2.882)	(0.964)	(1.831)
Post x Gig Intensity x High	15.41***	1,145***	4,633	4,863	5.805	-1.944	-2.349
	(2.007)	(183.7)	(4,067)	(6,854)	(9.415)	(2.087)	(4.661)
Observations (Unweighted)	169,618	169,618	169,618	158,194	169,618	169,618	169,618
Observations (Weighted)	2,751,043	2,751,043	2,751,043	2,591,119	2,751,043	2,751,043	2,751,043
R-squared	0.303	0.332	0.853	0.88	0.582	0.803	0.821
Pre-Period Dep Var Mean	0.01	0.49	42,388	66,483	91.09	1.09	3.27
Pre-Period Dep Var SD	0.83	175.06	28,890	48,400	28.49	10.40	17.78

Notes: Results presented are for the subsample of near-elderly and elderly workers, those ages 55 and above 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 and the year immediately after. 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 x 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 ($^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$).

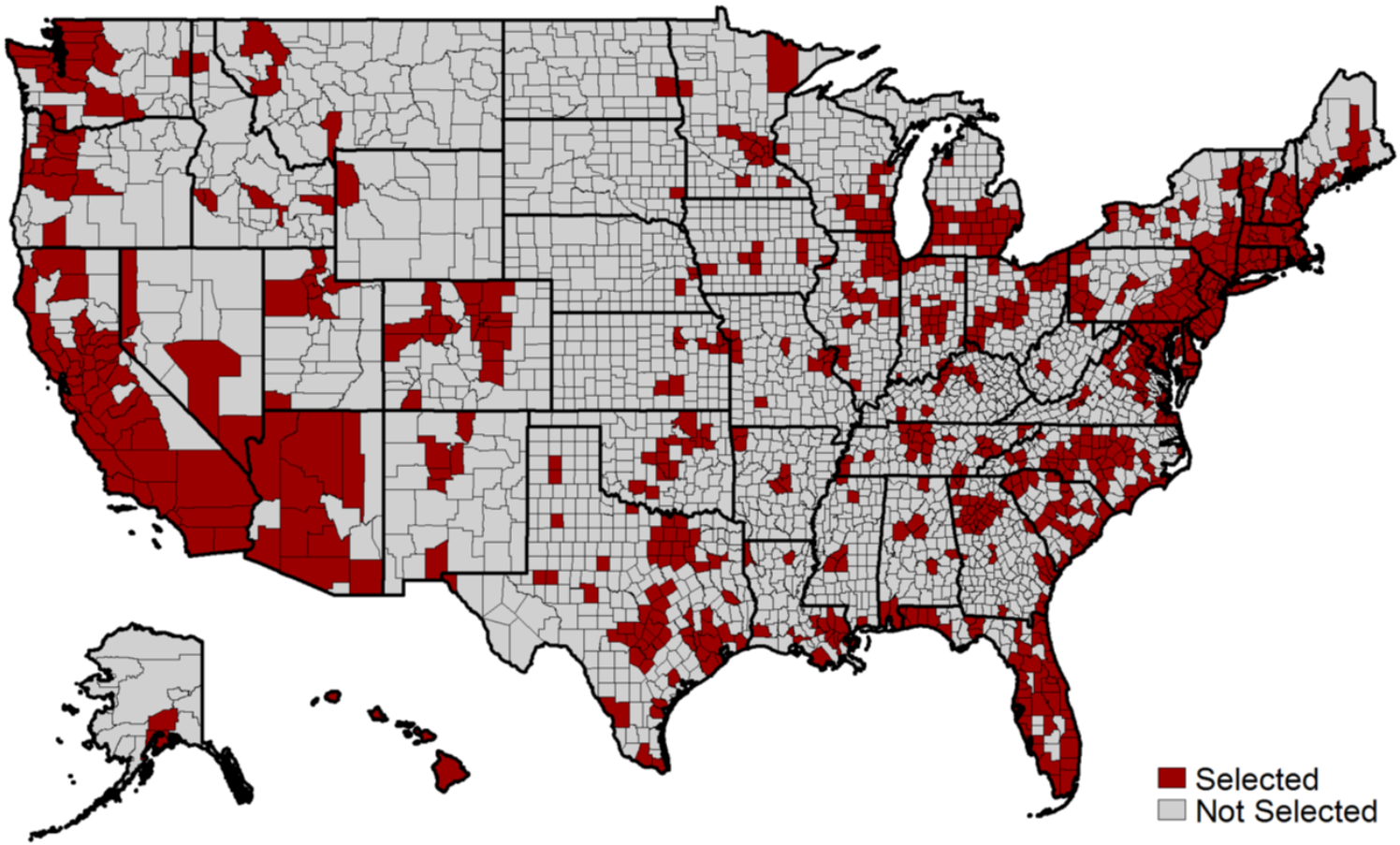
Table 8: Long Run Effects on Labor Supply, Income, and Social Insurance Receipt
(Near-Elderly and Elderly)

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	0.198***	35.98***	-11,178***	-11,323***	-34.91***	6.492***	6.540***
	(0.0641)	(12.71)	(847.4)	(1,345)	(1.552)	(0.700)	(0.861)
Post x Gig Intensity	0.428	46.18	-1,708	-8,715**	12.16***	-8.560***	6.297***
	(0.282)	(56.17)	(2,072)	(3,386)	(4.067)	(2.111)	(2.410)
Post x High	1.138*	-171.0	-2,376	-4,336	0.724	-0.825	0.524
	(0.603)	(107.8)	(2,032)	(3,185)	(3.640)	(1.641)	(2.422)
Post x Gig Intensity x High	33.15***	6,415***	6,324	10,177	4.541	-5.855*	-4.491
	(4.016)	(766.3)	(5,730)	(10,822)	(9.697)	(3.307)	(6.275)
Observations (Unweighted)	229,070	229,070	229,070	205,987	229,070	229,070	229,070
Observations (Weighted)	3,813,860	3,813,860	3,813,860	3,419,527	3,813,860	3,813,860	3,813,860
R-squared	0.328	0.326	0.783	0.828	0.590	0.630	0.820
Pre-Period Dep Var Mean	0.01	0.49	42,388	66,483	91.09	1.09	3.27
Pre-Period Dep Var SD	0.83	175.06	28,890	48,400	28.49	10.40	17.78

Notes: Results presented are for the subsample of near-elderly and elderly workers, those ages 55 and above 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 x 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 ($^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$).

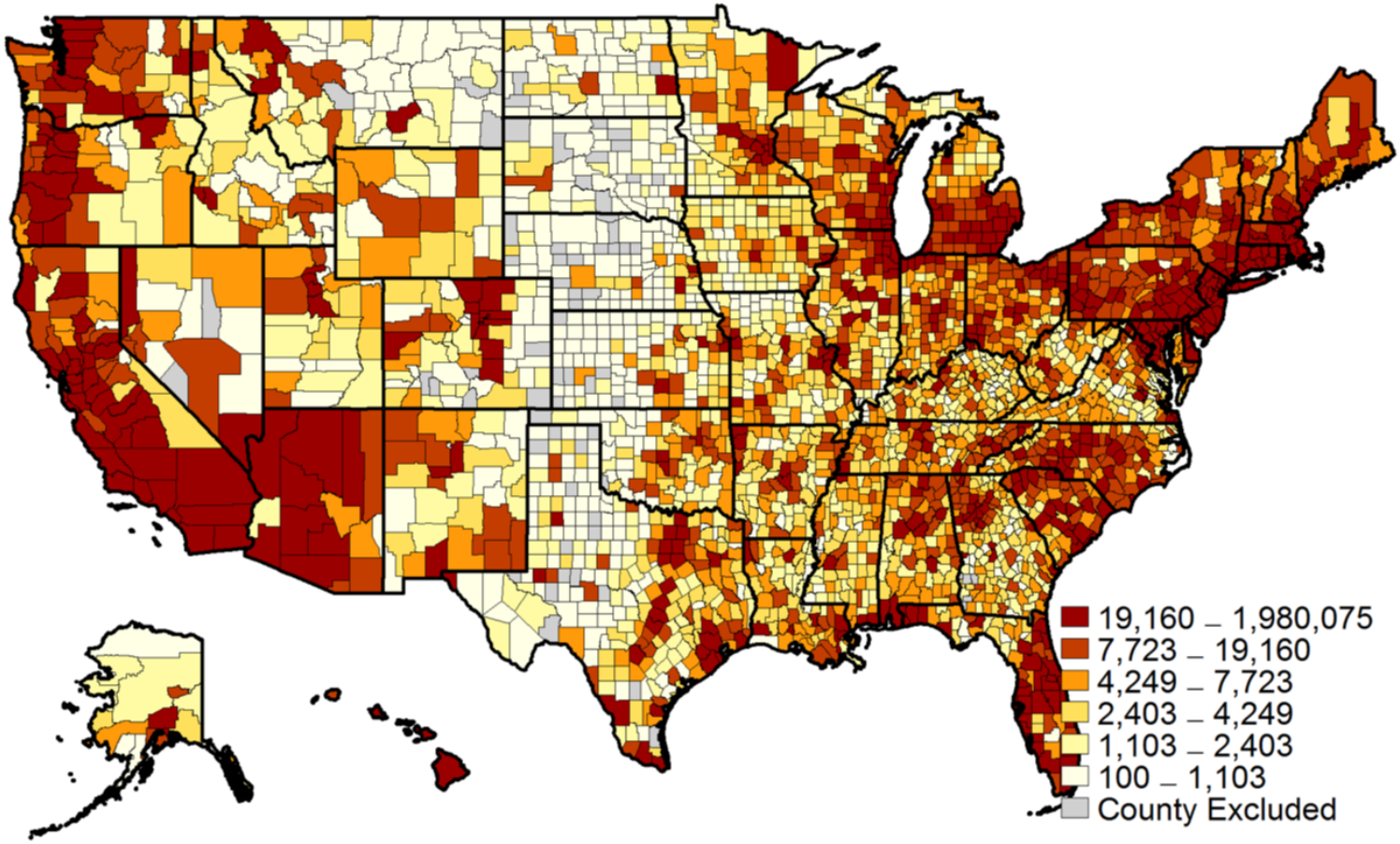
Appendix A Figures and Tables

Figure A1: County Selection



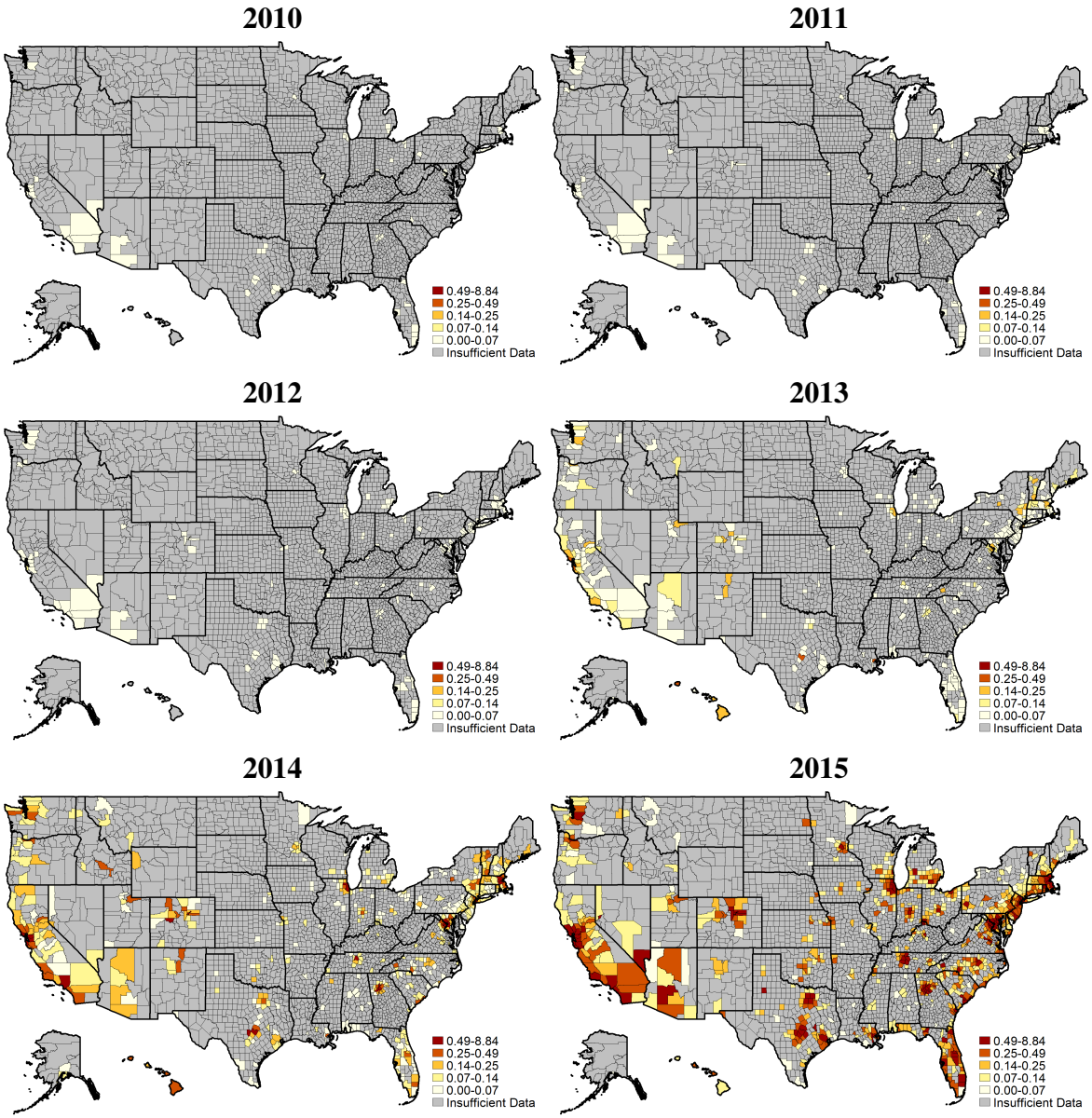
Notes: Counties in dark red had gig platforms enter by 2015. All individuals who become unemployed outside of these counties are excluded from the analysis sample.

Figure A2: UI Distribution by County



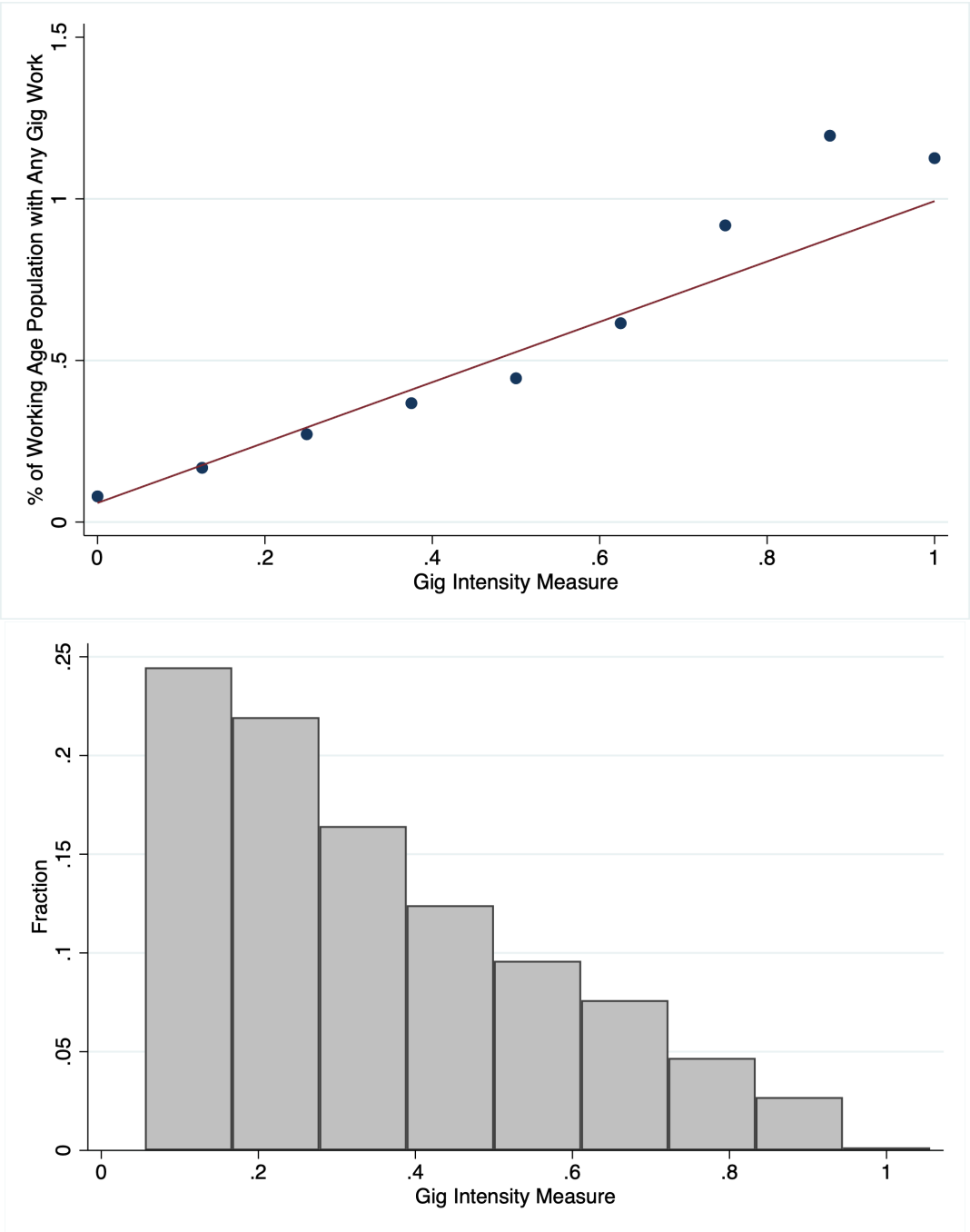
Notes: Counts indicate the number of UI events between 2008-2015 by each county.

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



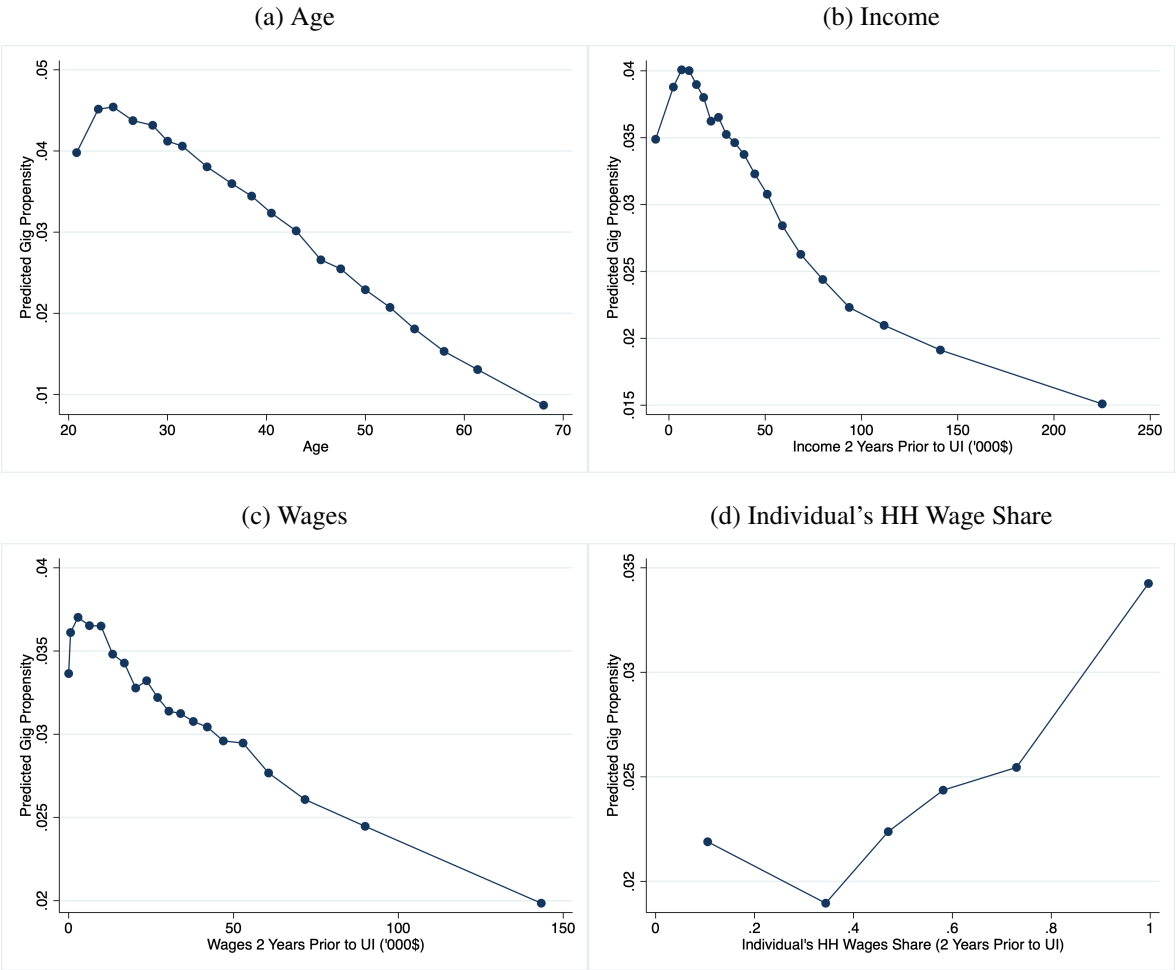
Notes: The above maps illustrate the geographic variation in gig platform availability at a given point in time across counties. Second, they illustrate variation within a county over time in the prevalence of gig work, as measured in the percent of the counties working age population with any amount 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: Linearity of Intensity Measure



Notes: Figure A4 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.

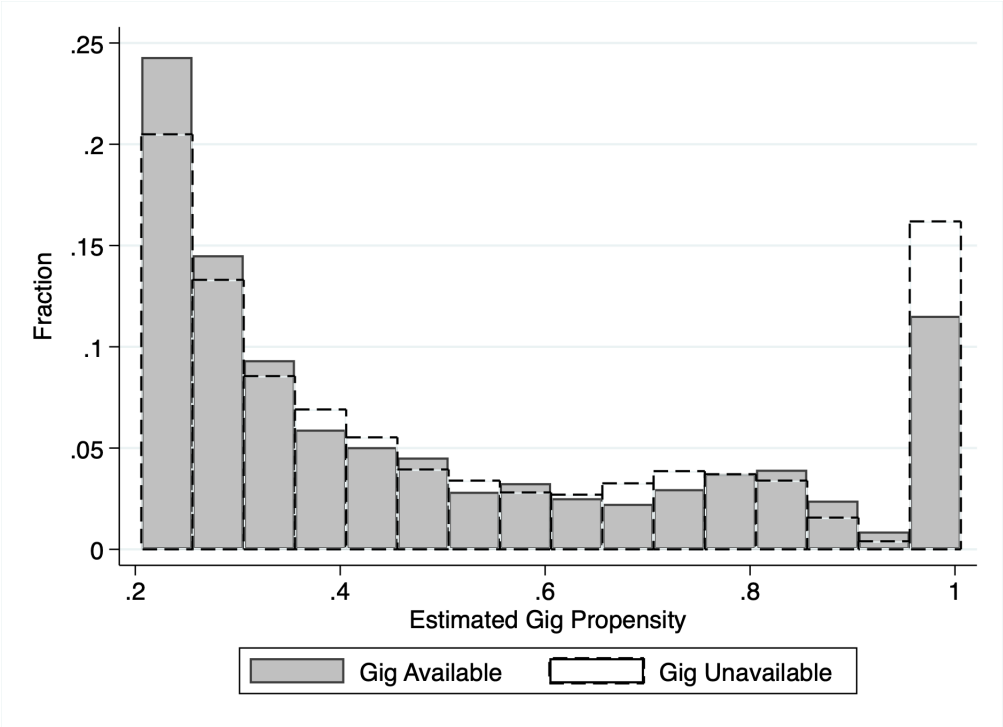
Figure A5: Predicted Gig Propensities with Respect to Key Predictors



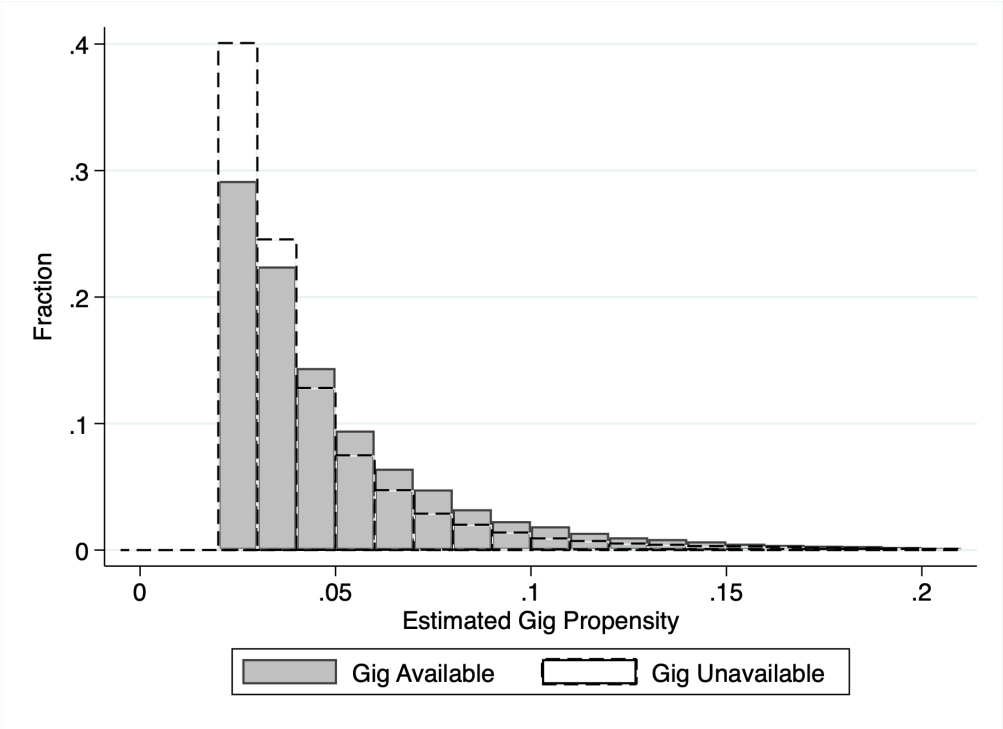
Notes: Age is at the time of UI receipt. Income is household AGI from Form 1040 for filers and the sum of information returns for non-filers (e.g. W-2s, 1099s, etc.). Wage Earnings are the sum of all W-2 wages. Individual household wage share is the an individual's wage earnings as a fraction of the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

Figure A6: Distribution of Gig Propensities by Gig Availability

(a) Among High Gig Propensity Individuals

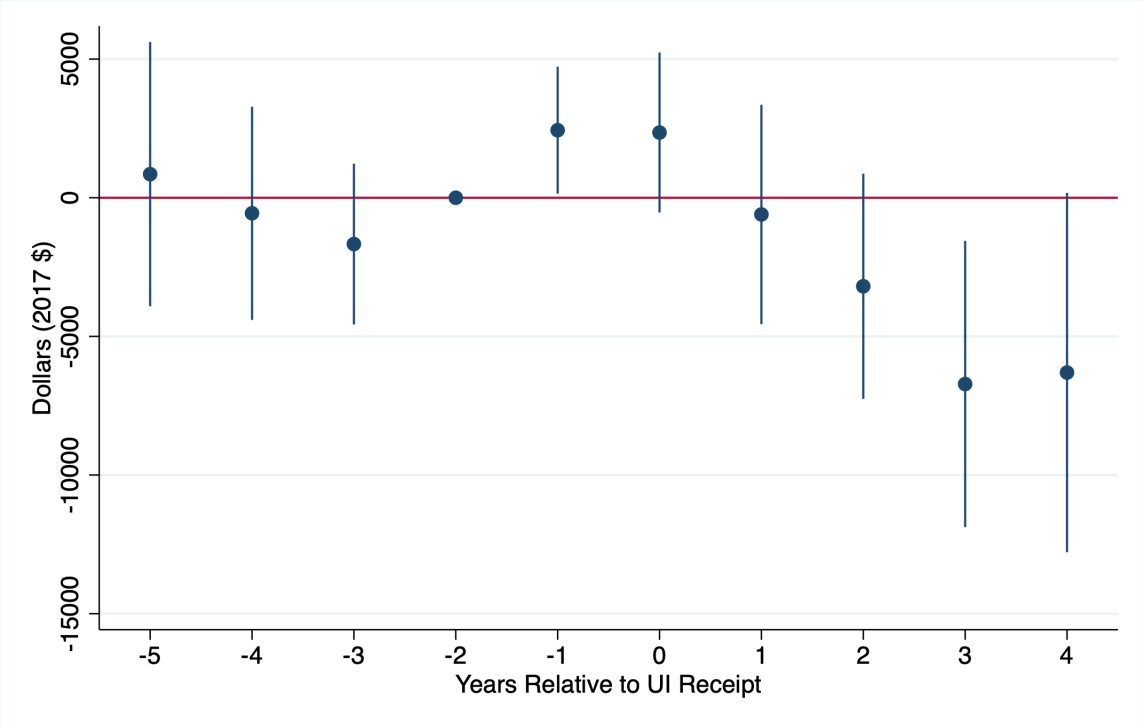


(b) Among Low Gig Propensity Individuals



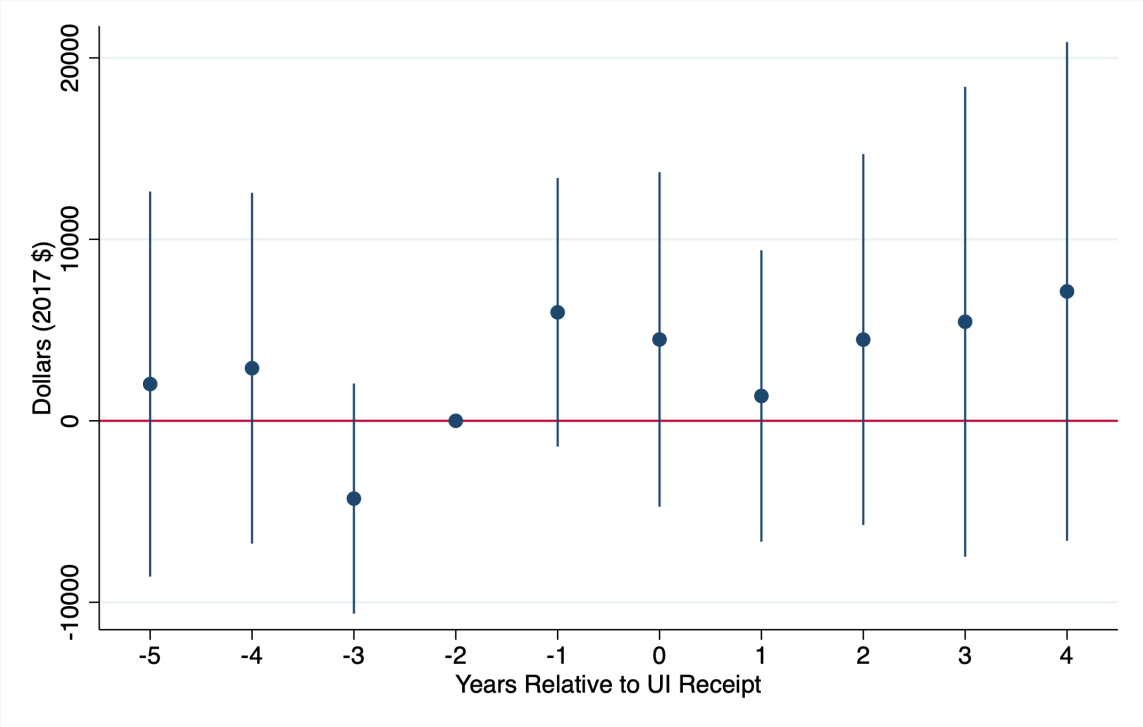
Notes: High gig propensity individuals have predicted propensity values > 0.2 and low gig propensity individuals have predicted propensities between 0.02 and 0.20.

Figure A7: 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. Sample balanced on event time $k \in [-3, 2]$. Regression includes individual FEs, county x 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.

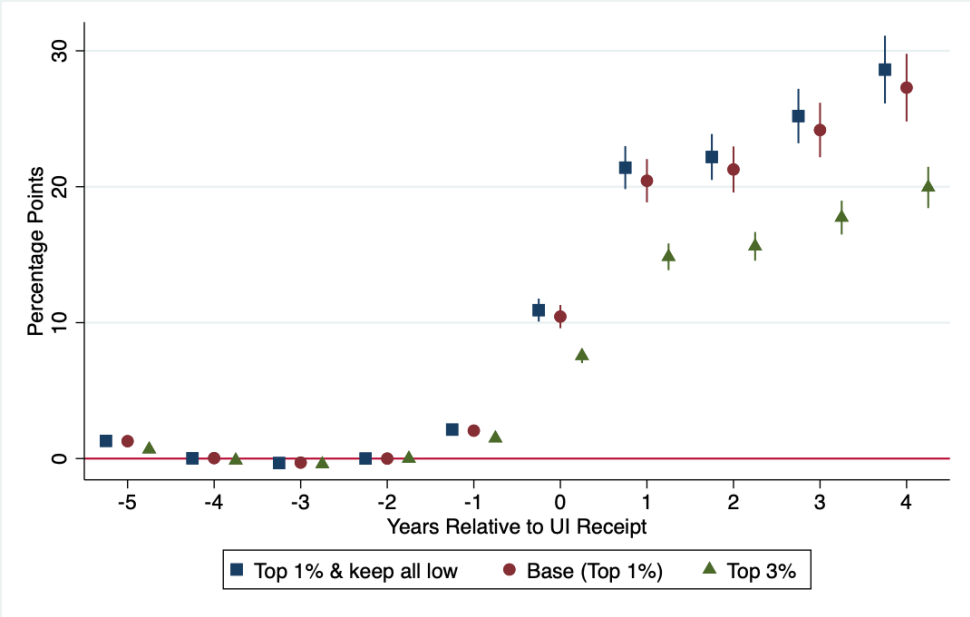
Figure A8: Yearly Coefficients for Individual Income
(Near-Elderly and Elderly)



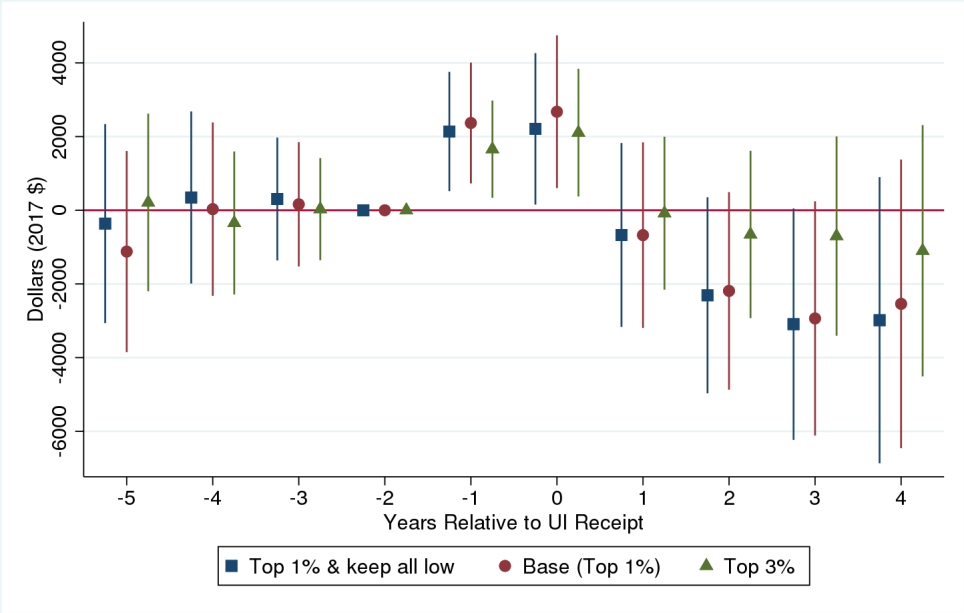
Notes: Dependent variable is individual income (2017 $), and the top and bottom 1% of values are winsorized. Restricted to near-elderly and elderly sample, ages 55 and above. Coefficient estimates for $T_{it}^{k} * G_i * H_i$ are plotted for each year in event time relative to event time k=-2. These 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. Sample balanced on event time $k \in [-3, 2]$. Regression includes individual FEs, county x 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 A9: Robustness to Definition of High and Low Gig Propensity
(Prime-Age Workers)

(a) Gig Year (x 100)

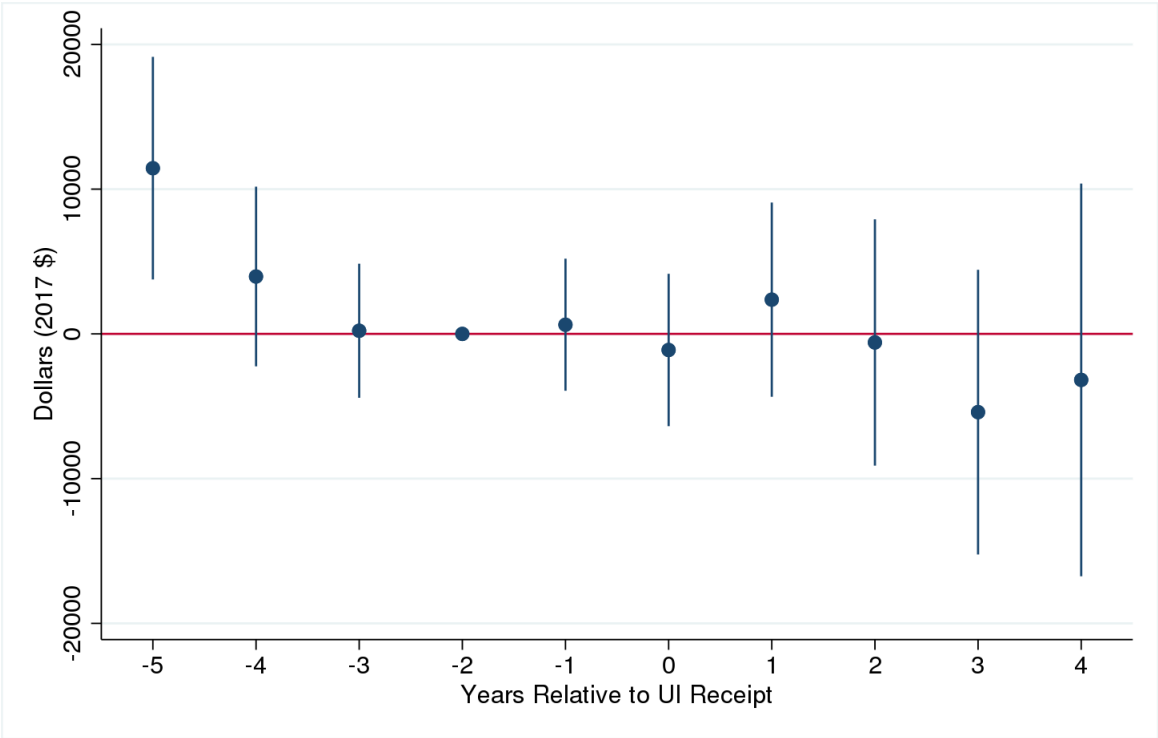


(b) Individual Income (2017 $)



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. Sample balanced on event time $k \in [-3, 2]$. Regression includes individual FEs, county x 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 A10: 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. Sample balanced on event time $k \in [-3, 2]$. Regression includes individual FEs, county x 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: Sample Restrictions: Numbers of Observations

	Sample		
	All Ages	Prime-Age	Near-Elderly
All UI Events 2005-2017			
Number of UI Events	68,510,061	49,034,010	10,279,954
Unique Individuals	53,073,619	37,274,944	8,916,938
...with 1 UI event	40,087,646	27,446,153	7,690,278
...with 2+ UI events	12,985,973	9,828,791	1,226,660
Restricting to First UI Event 2008-2015			
Number of UI Events	48,385,982	34,183,999	7,552,562
Unique Individuals	38,657,353	26,901,896	6,638,523
Unique Individuals (sample restrictions)			
First UI Event 2008-2015	38,657,353	26,901,896	6,638,523
Drop non-US counties	38,606,328	26,863,949	6,634,098
Drop never Gig Areas	34,911,640	24,357,943	5,996,141
Drop gig after 2015 areas	32,183,089	22,473,779	5,529,944
Final Stratified random sample			
Unique Individuals	1,176,784	869,702	111,971

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. Near-Elderly and Elderly workers are those ages 55 and above at the time of UI receipt. Each row denotes the number of observations or unique individuals in each sample restriction.

Table A2: Online Gig Platforms

Labor Platforms			
Amazon.com (NEC)	Greypoint	Postmates	Taskeasy
Angies List	Groop	Rasier *[aka Uber]*	Taskrabbit
Arise Virtual Solutions	Grubhub	Red Beacon	Thumbtack
Dogvacay	Handy	Ridecharge	Turo
Doordash	Helper Bees	Ridelabs	Uber
Fasten	Juno	Shipt	Unter *[aka Uber]*
Field Nation	Lasership	Shyp	Upwork
Flatiron Transit	Leap Force	Sidecar	Varsity Tutors
GettAround	Lyft	Spreadshirt	Vipkid HK
Gigwalk	Maplebear *[aka Instacart]*	Rover	Wag Labs
Glamsquad	Orderup	Takelessons	

Notes: This list includes the labor platforms compiled in my earlier work (Collins et al., 2019), and that I utilize in this paper to identify individuals with gig work.

Table A3: 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	-0.0174**	-0.245	-4,969***	-6,725***	-13,575***	-4.090***
	(0.00792)	(1.006)	(116.0)	(177.0)	(139.8)	(0.188)
Post x Gig Intensity	0.0265	-56.37***	343.0	-1,598***	-444.5	8.132***
	(0.0409)	(5.037)	(338.5)	(531.1)	(398.4)	(0.503)
Post x High	0.893***	47.35***	-54.89	-1,322**	659.5	-0.856
	(0.117)	(14.51)	(400.3)	(665.6)	(498.1)	(0.697)
Post x Gig Intensity x High	18.26***	2,044***	-801.7	-1,442	-2,210*	-1.957
	(0.761)	(103.4)	(1,138)	(1,831)	(1,293)	(1.811)
Observations (Unweighted)	5,197,453	5,197,453	5,197,453	4,655,166	5,197,453	5,197,453
Observations (Weighted)	78,845,929	78,845,929	78,845,929	70,398,195	78,845,929	78,845,929
R-squared	0.249	0.228	0.707	0.765	0.681	0.339
Pre-Period Dep Var Mean	0.01	0.33	32,856	46,655	34,101	92.8
Pre-Period Dep Var SD	0.78	95.57	25,749	40,249	29,630	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 x 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 A4: Pooled Effects on Labor Supply, Income, and Social Insurance Receipt
(Near-Elderly and Elderly)

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)
	Pooled (All Post Years)						
Post	0.0430	13.23*	-5,004***	-6,441***	-8.164***	0.770*	2.126***
	(0.0440)	(7.627)	(534.6)	(831.1)	(0.972)	(0.412)	(0.550)
Post x Gig Intensity	0.330*	-47.50	3,890***	3,545*	17.47***	-7.947***	1.814
	(0.187)	(30.62)	(1,364)	(2,128)	(2.493)	(1.215)	(1.526)
Post x High	0.571	-104.4	-1,750	-2,779	0.450	0.457	0.804
	(0.543)	(82.96)	(1,687)	(2,570)	(3.013)	(1.274)	(1.924)
Post x Gig Intensity x High	27.48***	4,390***	4,697	5,557	3.437	-5.706**	-3.098
	(3.562)	(562.3)	(4,405)	(7,797)	(8.040)	(2.410)	(5.331)
Observations (Unweighted)	304,548	304,548	304,548	274,361	304,548	304,548	304,548
Observations (Weighted)	5,062,884	5,062,884	5,062,884	4,551,458	5,062,884	5,062,884	5,062,884
R-squared	0.302	0.306	0.752	0.803	0.506	0.597	0.791
Pre-Period Dep Var Mean	0.01	0.49	42,388	66,483	91.09	1.09	3.27
Pre-Period Dep Var SD	0.83	175.06	28,890	48,400	28.49	10.40	17.78

Notes: Results presented are for the subsample of near-elderly and elderly workers, those ages 55 and above 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 x 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 Form 1099-MISC and Form 1099-K

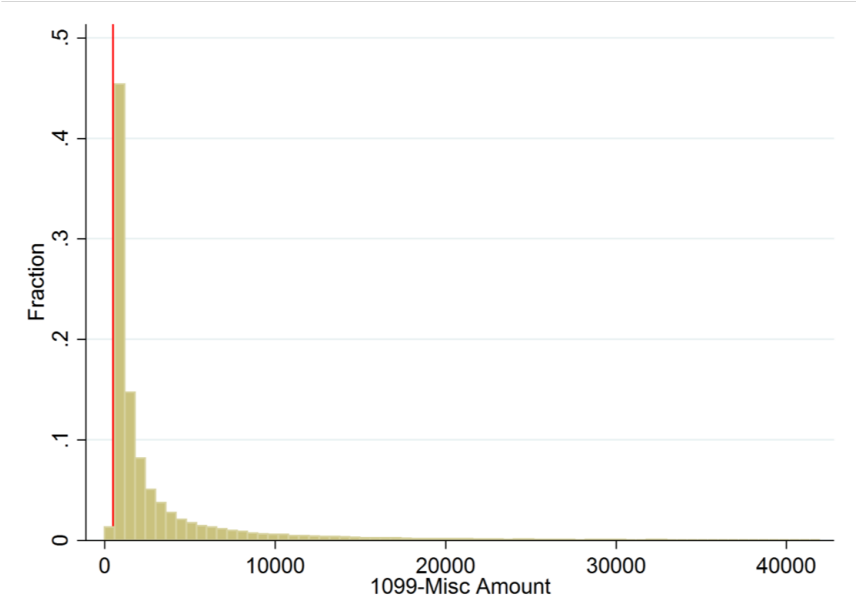
1099-MISC: IRS form 1099-MISC reports miscellaneous income. Of particular relevance is income that is reported on line 7, non-employee compensation, which includes payments for services that an individual provides when the individual is not an employee. This broadly includes all income earned as an independent 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, in practice individuals receive 1099-Ks below this threshold as well. I present the distribution of 1099-K by dollar amounts among gig workers in Figure B1.

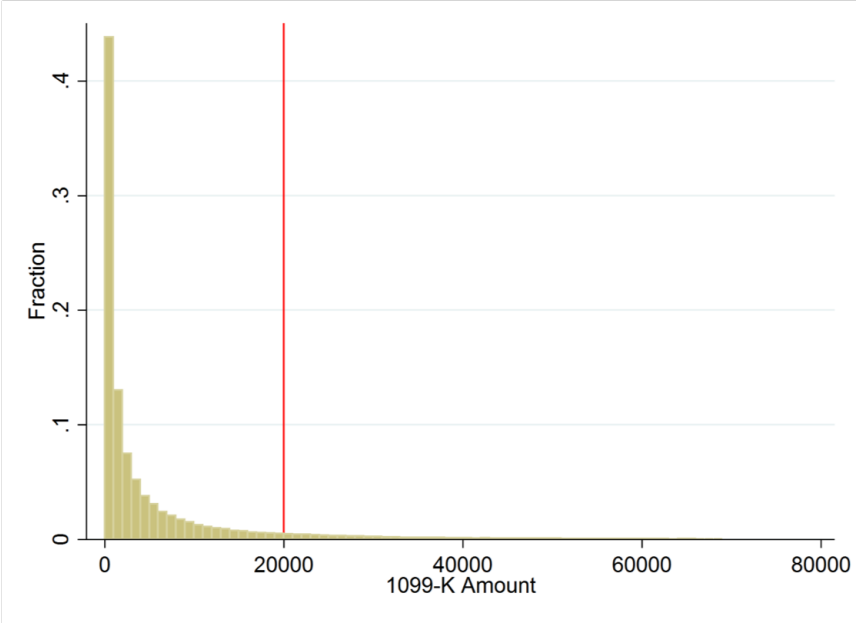
Schedule C: Schedule reports *Profit or Loss from Business (Sole Proprietorship)*. When filing, individuals self-report their "principal business or profession". In addition, I utilize information in these text strings to identify individuals who work in the online platform economy, however do not receive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

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.

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:

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

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.

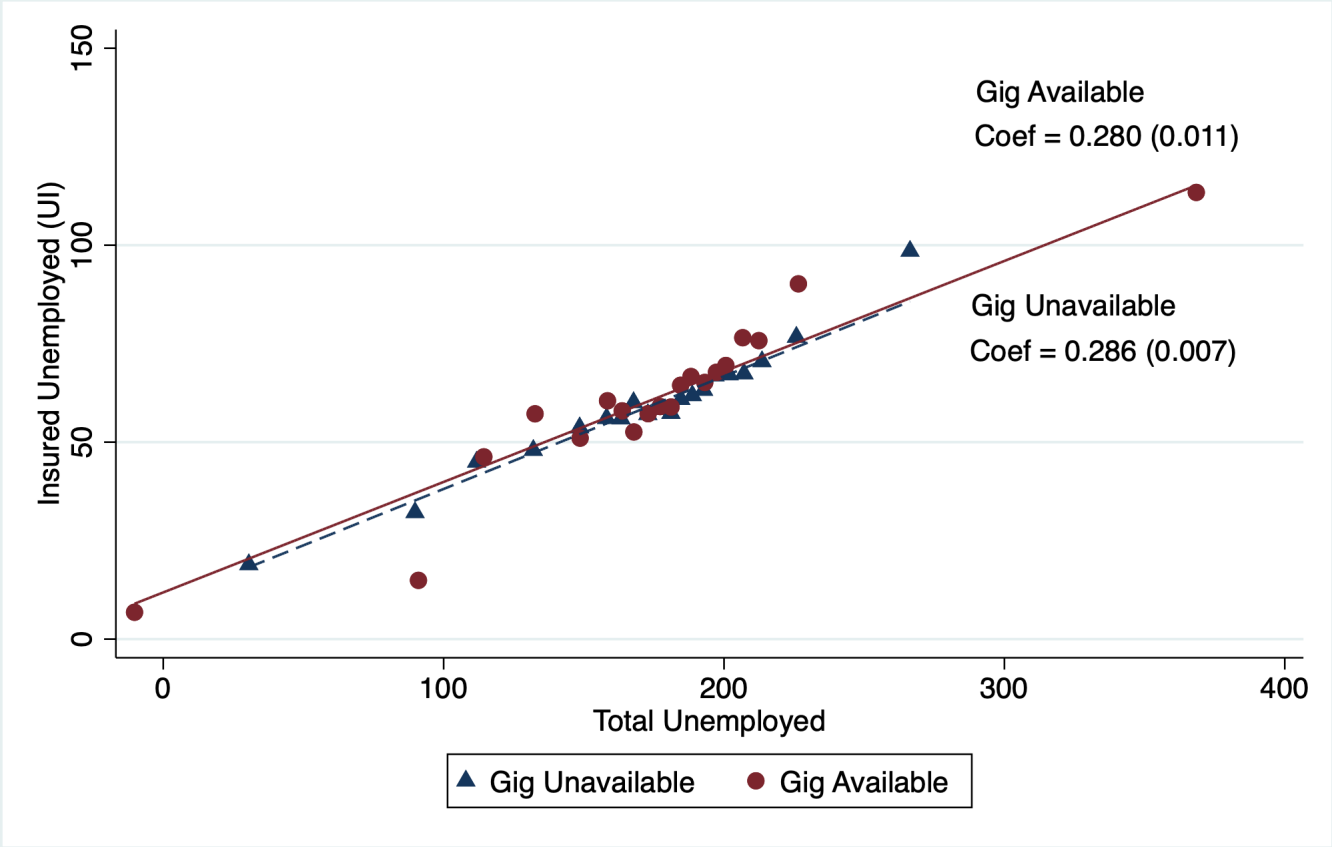
While gig availability does not appear to affect individuals decision to take up UI benefits, it may affect the duration of UI benefits and/or the amount of benefits that an individual receives. I examine this in Figure C2. While I do not find a statistically significant decrease in the total amount 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.[29]

Tables C1 and C2 present data on the characteristics of unemployment insurance applicants and

[29]The exact benefit formulas and how much income an individual can earn depends on each state's rules.

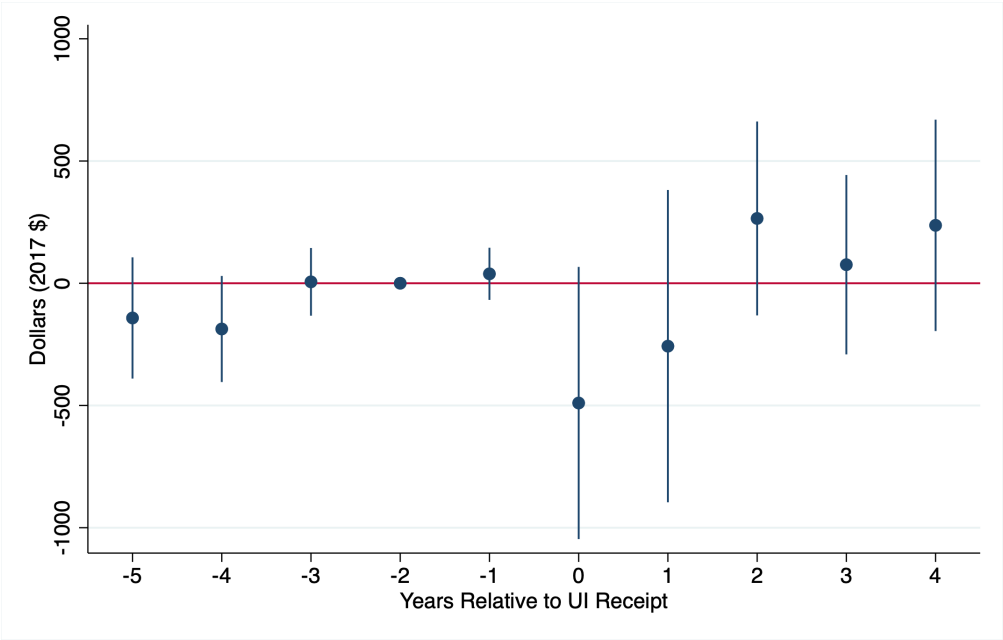
recipients from the Bureau of Labor Statistics (BLS). Table C1 provides summary characteristics on individuals by whether they apply for UI insurance to highlight differences and similarities between these two groups. Those who applied for UI in 2018 tended to be older, were more likely to be male, and 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 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. Sample balanced on event time $k \in [-3, 2]$. Regression includes individual FEs, county x 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

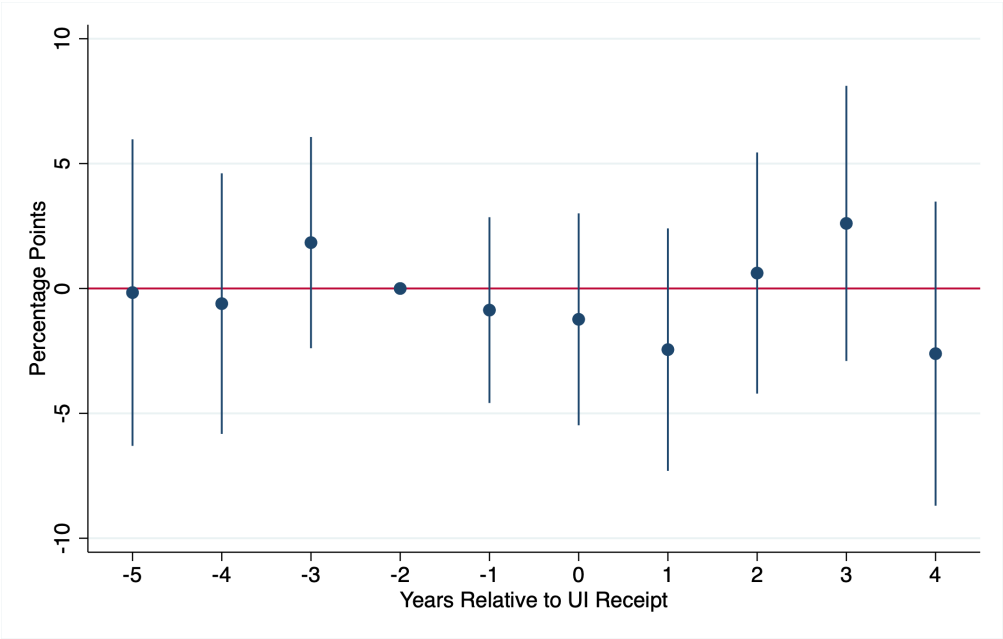
[1] Data exclude unemployed persons with no previous work experience and those who last worked more than 12 months prior to the survey.
NOTE: Estimates are an average of data collected in May and September 2018. Dash indicates no data or data that do not meet publication criteria (values not shown where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

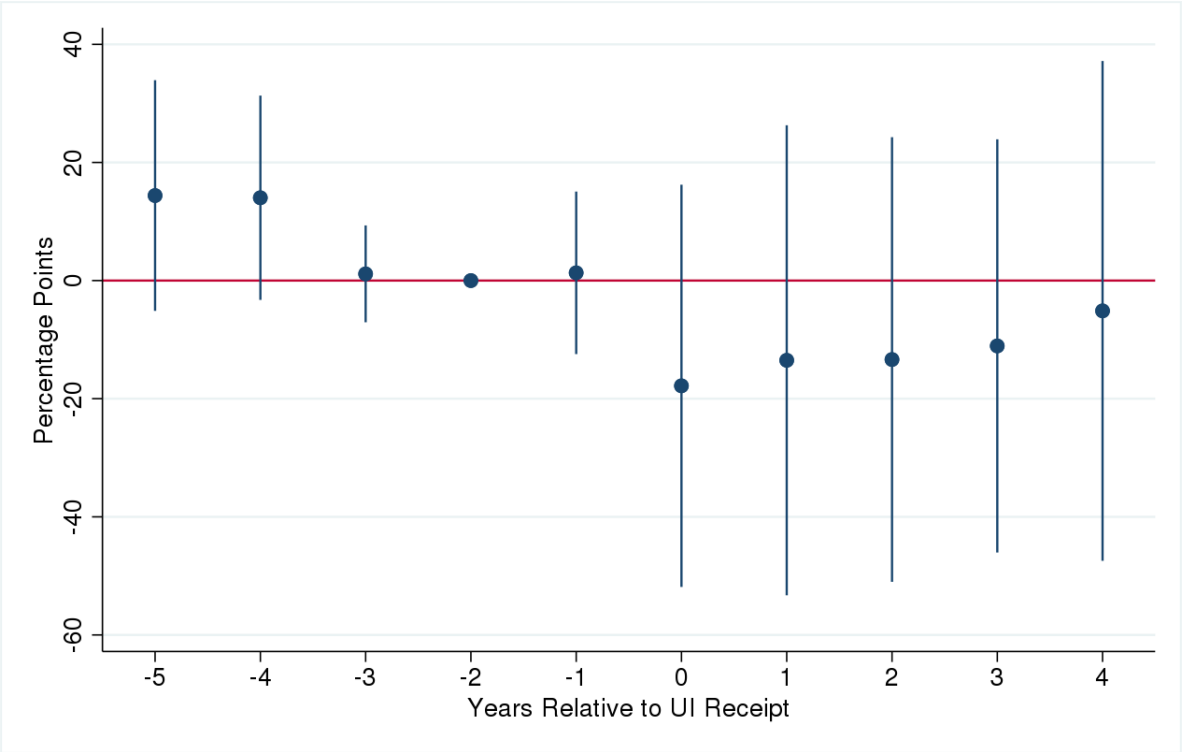


Notes: Dependent variable is an indicator for being a student in a given year as identified by having an eligible tuition payment on Form 1098-T (in percentage points 0 or 100). Coefficient estimates for $T_{it}^{k} * G_i * H_i$ are plotted for each year in event time relative to event time $k = -2$. Sample balanced on event time $k \in [-3, 2]$. Regression includes individual FEs, county x 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 12 and in column 7 of Tables 7, 8, and A4.

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 the near-elderly and elderly sample, 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. Sample balanced on event time $k \in [-3, 2]$. Regression includes individual FEs, county x 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—Near-Elderly and Elderly - Social Security Withdrawals

	(1)	(2)	(3)
VARIABLES	Has Soc Sec Ret (x 100)		
Post	9.982***	26.86***	13.12***
	(2.761)	(3.521)	(2.676)
Post x Gig Intensity	9.263	10.85	2.975
	(8.227)	(7.241)	(5.883)
Post x High	19.47**	1.972	6.999
	(8.312)	(6.285)	(5.974)
Post x Gig Intensity x High	-24.23	-13.39	-18.21
	(17.26)	(15.12)	(14.23)
Short Run (First Post Year)	X		
Long Run (Two-Four Years Post)		X	
Pooled (All Post Years)			X
Observations (Unweighted)	33,398	45,001	60,116
Observations (Weighted)	565,424	778,591	1,031,801
R-squared	0.805	0.877	0.809
Pre-Period Dep Var Mean	8.65	8.65	8.65
Pre-Period Dep Var SD	28.10	28.10	28.10

Notes: Results presented are for a subset of the near-elderly and elderly sample, 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 x 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 ($^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$).