



HOW DO OLDER WORKERS USE NONTRADITIONAL JOBS?

Alicia H. Munnell, Geoffrey T. Sanzenbacher, and Abigail N. Walters

CRR WP 2019-12
October 2019

Center for Retirement Research at Boston College
Hovey House
140 Commonwealth Avenue
Chestnut Hill, MA 02467
Tel: 617-552-1762 Fax: 617-552-0191
<https://crr.bc.edu>

All authors are with the Center for Retirement Research at Boston College (CRR). Alicia H. Munnell is director of the CRR and the Peter F. Drucker Professor of Management Sciences at Boston College's Carroll School of Management. Geoffrey T. Sanzenbacher is a research fellow at the CRR. Abigail N. Walters is a senior research associate at the CRR. The research reported herein was pursuant to a grant from the Alfred P. Sloan Foundation. The findings and conclusions expressed are solely those of the authors and do not represent the views of the Alfred P. Sloan Foundation or Boston College. This paper is released to inform interested parties of research and to encourage discussion. Any views expressed on statistical, methodological, technical, or operational issues are those of the authors and not necessarily those of the Alfred P. Sloan Foundation.

© 2019, Alicia H. Munnell, Geoffrey T. Sanzenbacher, and Abigail N. Walters. All rights reserved. Short sections of text, not to exceed two paragraphs, may be quoted without explicit permission, provided that full credit, including © notice, is given to the source.

Abstract

Working consistently through one's fifties and early sixties is key to attaining retirement security. However, workers also need access to retirement plans – so they can continue to accumulate resources – and health insurance – so they can avoid withdrawing assets in the event of a health shock. Workers without access to these benefits will likely struggle as they approach retirement, both financially and perhaps emotionally, as they deal with the stress of being unprepared. Yet, despite the fact that a large literature focuses on nontraditional jobs that often lack these benefits, it is unclear how older workers use these jobs and what the consequences are. If some older workers use nontraditional work for much of their late careers, then they likely will end up worse off. If, instead, older workers use nontraditional jobs only temporarily, then it is unlikely that their situation will substantially change. This paper uses the *Health and Retirement Study* to identify nontraditional jobs and relies on sequence analysis to explore how workers ages 50-62 use them. The results suggest that the majority of nontraditional jobs are used by workers consistently, and that fewer workers use these jobs briefly or as a bridge to retirement. In the end, workers consistently in nontraditional jobs end up with less retirement income than other workers and are more likely to be depressed, even controlling for their financial situation and depression prior to age 50. Given this situation, policymakers may want to consider ways to expand benefits to workers in these jobs to improve their well-being in retirement.

Introduction

While working consistently through one's fifties and early sixties is key to achieving retirement security, working – by itself – may not be enough. Workers in jobs that lack retirement and health benefits are at risk of a retirement income shortfall. Few households save for retirement outside of employer-sponsored plans, and poor health drains resources for those without health insurance. Yet, despite the increased focus on “nontraditional” jobs – jobs that usually lack these benefits – it is unclear how older workers use these jobs and how they might affect well-being approaching retirement.¹ If some older workers end up in nontraditional work for much of their later careers, then they likely will end up worse off financially, and perhaps emotionally too as they struggle with the possibility of a less secure retirement. If, instead, older workers use nontraditional jobs only temporarily before returning to traditional work or as a bridge to retirement, then it is unlikely that their situation will substantially change.

To gain a better understanding of the uses and impact of nontraditional jobs in workers' late careers, this project follows workers from ages 50 through 62 in the *Health and Retirement Study* (HRS), and determines at each age whether they are in a traditional job, a nontraditional job, not working, or retired.² The next step is to use sequence analysis to group older workers who have similar employment patterns, calculate the share following each pattern, and compare the personal characteristics of each group. Finally, the project will use the employment groupings from the sequence analysis as explanatory variables in two sets of regression analyses. The first set of regressions will focus on the effects of each sequence on the availability of retirement resources. The second set of regressions will look at a more holistic measure of well-being – the incidence of depression. The results will shed light on the ways in which older workers use nontraditional work, how the use of that work varies by socioeconomic status, and ultimately its impact on the workers' using it.

The remainder of the paper is organized as follows. The first section provides background on how older workers use nontraditional jobs late in their careers. The second section describes the data and provides details on how nontraditional jobs are identified in the HRS, and also offers a comparison to other estimates of the prevalence of these jobs. The third

¹ See Katz and Krueger (2016, 2019).

² In practice, not working is defined as earning less than \$5,000 per year, unemployed, or out of the labor force (which includes disabled individuals).

section describes the methodology behind sequence analysis as well as the regression formulations used, while the fourth section presents the results. The final section concludes that just 26 percent of the sample works in a traditional job with benefits throughout their 50s and early 60s – this “ideal” pattern of employment is just not that common. Of the remainder, four patterns emerge: 1) those who retire well before age 62 (21 percent); 2) those who are only weakly attached to the labor force (16 percent); 3) those who work consistently, but in nontraditional jobs (11 percent); and 4) those who work consistently and mainly in traditional jobs, but with brief periods of nontraditional work or not working (26 percent). Regarding their well-being, individuals in nontraditional jobs consistently have lower projected retirement income and are more likely to experience depression than otherwise similar individuals who are in traditional jobs consistently, even conditional on their lifetime income and incidence of depression at age 50. Expanding benefits to workers in these jobs – for example, through access to retirement savings vehicles such as state-level auto-IRAs – may therefore be a valuable policy goal.

Background

Despite the possibility that nontraditional jobs could occur at any time in a worker’s late career, almost all research on how nontraditional work fits into late-career employment patterns has been focused on jobs that serve as a stepping-stone to ease the transition into retirement.³ Johnson and Kawachi (2007) find that older workers who switch jobs near retirement are likely to end up in a nontraditional job that does not offer benefits, but also report greater satisfaction with those jobs, in part due to less stress and lighter physical demands. Some evidence also exists that workers use these lower-compensating jobs to gain flexibility in their schedules as they approach retirement (James, Swanberg, and McKechnie 2011). Indeed, Cahill, Giandrea, and Quinn (2011) find that more than 60 percent of older workers who left full-time career jobs moved to this sort of “bridge job.” In other words, this literature would suggest that using nontraditional jobs as a transition to retirement may be somewhat common.

A limited literature also suggests that some older workers use these jobs more frequently. Specifically, research shows that workers who were in nontraditional jobs for an extended period have difficulty transitioning back to traditional work (Fournier et al. 2011). For example, about

³ Quinn and Burkhauser (1990) and Ruhm (1990) provide early reviews of partial retirement and bridge jobs.

one-fifth of temporary workers become trapped in a “precarious job carousel” where they cycle between bad jobs and no jobs (Barbieri and Scherer 2009; Fuller and Stecy-Hildebrandt 2015). However, it is unclear exactly how common this outcome is for older workers specifically.

While researchers have not focused on how older workers use nontraditional jobs in their late-career working patterns, other work has used sequence analysis to investigate labor force participation at older ages more generally. For example, Calvo, Madero-Cabib, and Staudinger (2017) use sequence analysis to examine how workers’ labor force status evolves in their 60s. Their analysis considers full- and part-time employment and non-employment to show that few workers follow the transition from full-time work to complete retirement at age 65. Instead, the retirement process is much more diverse and includes early and late retirement, as well as people who remain partly retired all the way up to age 70. However, their study does not consider the traditional or nontraditional nature of any jobs and does not focus on the 50s, a time of life when people should be working to prepare for a secure retirement.⁴

Data

Given the lack of research on the use of nontraditional jobs throughout late careers, this paper uses the 1992 to 2016 waves of the *Health and Retirement Study* (HRS), a biennial longitudinal survey of older Americans to characterize workers’ labor force patterns from ages 50 through 62 and to see how nontraditional work fits in. The sample consists of members of the Original HRS, War Baby, and Early Baby Boomer birth cohorts, for whom data on work history are currently available through age 62. Although the analysis seeks to follow workers from ages 50 to 62, to increase the sample size the paper also includes those entering the HRS at 52 and imputes these individuals’ age 50 work status.⁵ The sample is further restricted to respondents who live to at least 62, do not otherwise exit the HRS prior to 62, do not have missing demographic variables (described below), and work at least one time between ages 50-62. Within this sample, some people are missing information for individual waves – if this omission happens for three or more waves the individual is dropped from the analysis; if it is for two or

⁴ Gustman and Steinmeier (2000) also examine patterns of full-time work, partial retirement, and complete retirement but do not use sequence analysis; their analysis is limited to the first four waves of the HRS, so the number of potential patterns is more manageable.

⁵ All imputations are carried out using STATA’s mi (multiple imputation) framework, as described in Halpin (2013).

fewer waves then their work status is imputed for the missing periods. The final sample consists of 4,174 respondents (see Table 1 for detail on the exclusions).

Once the sample is identified, the next step is to identify each individual's work status at each wave from ages 50 through 62. For the sequence analysis, each individual is assigned one of four statuses in each wave: 1) not working (but not retired); 2) retired; 3) working in a traditional job; and 4) working in a nontraditional job. Not working is defined as earning less than \$5,000 a year but not claiming to be fully retired.⁶ "Retired" is defined as not working and classified as retired by the RAND labor force status variable. Among those who are working, the key distinction is between traditional and nontraditional work. The issue is how to define nontraditional work.

Defining Nontraditional Work

Defining nontraditional work is complicated – an agreed upon definition does not exist, and different definitions yield vastly different estimates. Much of the existing literature has defined this type of work based on the nature of the relationship workers have with employers. Using this approach, researchers have come up with a wide range of estimates. The narrowest definitions of nontraditional work are limited to workers in the "gig economy" (e.g., Uber, Task Rabbit) or in short-term employment relationships.⁷ These groups include just 1 percent and 2 percent of workers, respectively.⁸ At the other extreme, the U.S. Government Accountability Office's broadest concept, which includes the self-employed and those in part-time jobs, covers 31 percent of the workforce.⁹ In between these extremes is the definition of "alternative" work used by the Bureau of Labor Statistics (BLS) – which has received considerable attention through research by Katz and Krueger.¹⁰ The BLS definition includes independent contractors and workers who are either with a temp agency, employed by a contract firm, or on-call. Under this definition, the prevalence of nontraditional work hovers around 10 percent. Another definition in between the two extremes is that of "1099 workers," as used in a 2019 study by

⁶ This definition also includes those who claim not to be working because they are disabled, unemployed, or otherwise out of the labor force.

⁷ Short-term jobs are defined as expected to last less than one year.

⁸ See Farrell and Grieg (2016); U.S. Bureau of Labor Statistics (2018); and Collins et al. (2019).

⁹ U.S. Government Accountability Office (2015).

¹⁰ Katz and Krueger (2016, 2019).

Collins et al. These workers are self-employed individuals who work for firms (i.e. freelancers and “gig” work) but do not fall under normal employment classification rules, and file 1099 tax forms. Using this definition, nontraditional work would account for 11.8 percent of the workforce.¹¹

Regardless of how nontraditional jobs are defined, the common thread is that they often lack basic benefits, such as health insurance and retirement plans, and/or have volatile earnings and employment. For this reason, our analysis adopts a more direct measure of nontraditional jobs based on such job characteristics. Specifically, the analysis will define nontraditional work in two ways: 1) broadly as any job lacking both health insurance and retirement benefits; and 2) more narrowly as a job without these benefits that also has some measure of job instability.¹² In the HRS, these characteristics can be identified for an individual’s current “main” job at the time of their HRS interview. Because these characteristics cannot be easily identified for jobs held in between HRS interviews, the sequence analysis is limited to “snapshots” of individual’s employment status at the seven interviews occurring between ages 50 and 62.¹³

Given the variation in prevalence across the various definitions, it is useful to see how a definition based on job characteristics like benefits compares to the more employer-employee relationship definitions from the existing literature. To ensure an accurate comparison, the analysis requires a dataset with questions on both the worker-employer relationships used in the other definitions presented above, and job characteristics like the availability of benefits that are used in this paper. For this purpose, the BLS’s *Current Population Survey* (CPS) is the best source.

For the comparison of the various definitions that exist in the literature to the one used in this paper, we first compute the share of workers ages 50-62 in 2017 who are in employer

¹¹ Collins et al. (2019).

¹² One potential problem with identifying health insurance being offered by an employer is that the line of questioning in the HRS only asks if individuals are covered by their employers’ plan, not whether they are offered it. So married individuals with coverage through their spouse would look like they are not offered health insurance. Looking at the CPS, it turns out roughly 70 percent of married individuals with health insurance through their spouse were also offered it at their job – we assume that if a person’s spouse has employer health insurance that they were offered coverage through their employer. This approach provides a conservative estimate of nontraditional work.

¹³ While the questions necessary to derive the nontraditional definition used in this paper are only asked about the main job, it seems unlikely that individuals would have health and retirement benefits through a job that they do not consider to be their main source of employment, so any effect on the sequence analysis of focusing on the main job is likely to be limited.

relationships under the standard BLS definition. Next, the share of workers in jobs without health insurance and retirement benefits is calculated – i.e., our broad “no benefits” definition of nontraditional work (unfortunately, the CPS does not have the right variables to get at the measures of instability used in the narrow definition). Under the BLS measure, 11 percent of workers in 2017 were in nontraditional jobs, compared to 20 percent under the broader no-benefits measure (see the solid bars in Figure 1, which also includes other definitions for additional context). The estimates in Figure 1 are for a single point in time. Figure 2 compares the two measures over 1994-2016, and it still finds a large and persistent gap.

Given the considerable gap between the two definitions of nontraditional work, the question is: which does a better job of picking up the vulnerable workers that researchers are concerned with? It turns out, compared to the workers defined as nontraditional under the BLS definition, the additional workers picked up by the broader no-benefits definition tend to have shorter job tenure and lower socioeconomic status (see Table 2).¹⁴ The basic issue is that the BLS definition includes many independent contractors, and those individuals tend to have been employed in that type of work for a while with relatively high incomes even though they may lack benefits.¹⁵ By picking up many employees working without benefits instead of workers who lack benefits only because they employ themselves, the definition used in this paper and based on the presence of benefits picks up more vulnerable workers than the BLS measure, making it a better choice for this paper.

Given that the benefits-based definition used in this paper seems to appropriately capture vulnerable workers, it is worth exploring how the definition looks in the longitudinal data needed to do sequence analysis – the HRS. Reassuringly, the HRS data show that the percentage of workers ages 50-62 in jobs with no benefits is generally similar to that using the CPS data despite a noticeable difference early in the period (see the gray versus the red lines in Figure 3).¹⁶ As noted above, the concern over nontraditional jobs stems not just from a lack of benefits, but

¹⁴ The *Current Population Survey May Supplement* does not ask earnings questions for all workers.

¹⁵ Authors’ calculation from the CPS. For example, the median tenure for an independent contractor ages 50-62 is 15 years, much higher than for the typical worker, and they have an average household income of \$85,000, similar to traditional workers under the BLS definition.

¹⁶ The definition shown in Figure 3 defines nontraditional as lacking benefits. Another approach would be to use the longitudinal nature of the data to see if the job *ever* offered those benefits. Such an approach reduces the share of those in nontraditional jobs by 3-4 percentage points. This approach is not used as the default since it seems relevant that the person said the job was lacking those benefits in a given year.

also a lack of stability in earnings or employment. Some of the jobs that lack benefits will be stable, and these workers may be less vulnerable. So, the paper also uses a more narrow definition that takes into account job stability. This definition will count a job as nontraditional if it lacks benefits and: 1) has hours that are variable at some point during the job; or 2) if the worker is self-employed with no benefits and with no employees.¹⁷ Under this definition, the percentage of jobs that are nontraditional falls from 16.9 percent to 7.6 percent, somewhat lower than the standard BLS definition of nontraditional workers.

Methodology

With each worker assigned a status as not working, retired, working in a traditional job, or working in a nontraditional job, the next step is to identify various patterns of work for ages 50-62 using sequence analysis. Then, the project turns to analyzing the relationship between these employment sequences and retirement resources using a regression analysis.

Sequence Analysis

Sequence analysis is a relatively novel technique in the social sciences; its strength is that the outcome of interest is an individual's entire employment history rather than employment status or job transition at a given age. The goal of sequence analysis is to group together workers with similar employment statuses at similar times and in a similar order. Consider the hypothetical example below, which shows how three workers move between traditional work (T), nontraditional work (N), not-working (U), and retired (R).

Example 1. *Employment Sequences for Hypothetical Workers*

	Age						
	50	52	54	56	58	60	62
Worker A	T	T	N	N	T	T	R
Worker B	T	T	N	T	T	T	R
Worker C	T	T	N	N	N	U	R

¹⁷ The study includes the self-employed with no benefits and with no employees as nontraditional work to capture those who run a small business or are independent contractors.

In this example, the sequence analysis will likely group workers A and B together, because they both started as traditional workers, used nontraditional work temporarily before returning to traditional work, and then retired at the same age. The only difference is small: how long they experienced nontraditional work. That experience differs distinctly from the pattern for worker C, who moved from traditional to nontraditional work at the same age as A and B, and retired at the same age, but never returned to traditional work.

In more technical terms, sequence analysis compares all of the sequences for sample members and constructs a matrix of how different each sequence is from the others. The difference between sequences is based on the minimum number of modifications needed to transform one sequence into another. A modification can take one of two forms. The first form is a substitution in which the state of one sequence is changed to match the state from another (e.g., changing work status at age 56 from nontraditional to traditional so that workers A and B have the same sequence). The second form is an insertion or deletion. An insertion occurs where a state is plugged into a sequence and every other state pushed back one wave to an older age. A deletion occurs when a state is removed and every subsequent state pulled forward to a younger age. Insertions and deletions typically happen simultaneously: a state is inserted and another state is deleted to preserve the number of observations.

To determine the difference between two sequences, the analysis follows the literature and uses optimal matching analysis (OMA). OMA requires that each substitution and insertion or deletion be assigned a “cost” to calculate the difference between sequences. The simplest way to calculate these differences would be to add up the number of substitutions and insertions/deletions – in other words to assign a uniform cost of one – but this approach has several disadvantages. Most notably, it does not recognize that some substitutions reflect much bigger changes than others – e.g., substituting a traditional job for a person who is not working at all may be a bigger leap than substituting a status of retired. Simply assigning substitution costs based on theories of which transitions are more likely to run the risk of being highly arbitrary, so this project uses an intuitive metric. Observed transition probabilities – transitions that are observed frequently in the data – e.g., from not working to retired – are assigned a lower substitution cost than those that are uncommon. Once substitution costs are assigned, this paper

follows the approach commonly taken in the literature and sets the cost of insertions/deletions to one-tenth of the highest substitution cost.¹⁸

The end result of OMA is a so-called pairwise distance matrix, which contains the sum of the costs of all substitutions and insertion/deletions required to transform each sequence into another. To group similar sequences together, a Hierarchical Cluster Analysis is used to detect groupings among the individual sequences with respect to their pairwise distances.¹⁹ The last step is to determine the number of groups for the analysis to detect. To choose the number of groups, the process was run assuming 2 through 12 groupings, with the final choice reflecting the number that maximized the Caliniskin and Harabasz index such that the resulting sequences made theoretical sense.²⁰

Regression Methodology

With the sequences in hand, the next question is how individuals' employment patterns relate to their available retirement resources and their emotional well-being at age 62. The issue is that people experiencing different patterns of non-employment, retirement, traditional work, and nontraditional work in their 50s and early 60s will also have different initial characteristics that may cause them to fall into those sequences, and those initial characteristics are likely to affect both their preparedness and their emotional well-being.

For example, workers frequently doing nontraditional work may have less education and therefore contribute less to retirement accounts even when they have the resources. Failure to control for education would therefore exaggerate the negative role of a sequence showing frequent nontraditional work – i.e., these workers would indeed have less, but some of the effect would be due to their education level. Or, workers who spend their late careers in nontraditional jobs may have spent their early careers in these jobs too, leading to less pension coverage earlier

¹⁸ Assigning the insertion and deletion cost to one-tenth of the highest substitution cost tends to create sensible sequence groupings (MacIndoe and Abbott 2004; Hollister 2009).

¹⁹ Specifically, the project used Ward's hierarchical clustering linkage criteria to group sequences that are similar to each other such that the groupings minimize the difference between sequences within the group and maximize the difference between sequences among the groups.

²⁰ The Caliniskin Harabasz index is a measure of the extent to which sequences within clusters are similar to one another and sequences across clusters are dissimilar (Cornwell, 2015). Specifically, the index is the ratio of the *between group* sum of squared differences to the *within group* sum of squared differences. Sequence analysis is vulnerable to claims that the results are the consequence of an ad hoc trial and error. To test the validity of the results, this paper used different cost assignments and dropped imputed respondents and achieved similar results. For critiques of sequence analysis and responses to those critiques, see Aisenbrey and Fasang (2010).

in life or lower lifetime incomes and therefore lower retirement income. In this case, it would not necessarily be the late-career experience of these jobs driving poor outcomes, but earlier experiences as well. On the emotional health side, if workers who are able to maintain traditional employment throughout their 50s and early 60s were less likely to be depressed entering their late careers, then failure to control for age 50 emotional health would exaggerate the benefits of the traditional work sequence. Therefore, controlling for both demographic characteristics and an individual's initial state (i.e., prior to age 50) regarding financial or emotional health is crucial to understanding how the late-career use of nontraditional jobs impacts well-being approaching retirement.

The paper therefore estimates two sets of regressions in which the individual's assignment of a sequence group serves as the independent variable of interest. The first set of regressions use retirement income at age 62 as the dependent variable. These regressions are estimated as quantile regressions at the median to lessen the impact of outlier levels of retirement income and control for demographics and initial health, the availability of retirement plans, and lifetime income prior to late career. The complete equation to be estimated is:

$$R_{i,62} = \beta_0 + \sum_{j=2}^K \gamma_j S_{i,j} + X'_{i,50} \beta + \delta H_{i,50} + \theta RP_{i,50} + \rho LI_{i,50} + \tau_i + \varepsilon_i$$

where $R_{i,62}$ is the log of the individual's retirement income at age 62: defined benefit pension income, Social Security benefits, and annuitized defined contribution plan and other financial wealth.²¹ The variable $S_{i,j}$ is an indicator for whether person i was assigned to sequence group j . Therefore, γ_j is the predicted percentage point change in median retirement resources associated with being in sequence group j relative to the base sequence group, which is assigned as the one with the highest amount of traditional work. The vector $X'_{i,50}$ contains demographic characteristics that could ultimately affect an individual's preparedness, like education, gender, race/ethnicity, and their age-50 marital status.²² $H_{i,50}$ is an index of the individual's initial health at age 50 that is based on objective measures, with higher values indicating worse health,

²¹ Social Security wealth is obtained based on RAND imputations that use Social Security administrative data. Defined-contribution and financial wealth are assumed to be annuitized at a rate consistent with private market data from ImmediateAnnuities.com.

²² For those who are not observed at age 50, the closest wave to age 50 is used.

whereas τ_i enters year of sample entry fixed effects.²³ Finally, $RP_{i,50}$ and $LI_{i,50}$ are coverage by retirement plans and lifetime income, respectively, at age 50.

The second set of regressions is similar to the first, except that the dependent variable here is the incidence of depression and the controls include depression prior to late career instead of lifetime income. These regressions are estimated as a probit, with average marginal effects reported in the results section below. The full specification to be estimated is:

$$D^*_{i,62} = \beta_0 + \sum_{j=2}^K \gamma_j S_{i,j} + X'_{i,50} \beta + \delta H_{i,50} + \theta RP_{i,50} + \rho D_{i,50} + \tau_i + \varepsilon_i$$

Where $D^*_{i,62}$ is the latent propensity of the individual to be depressed at age 62, $D_{i,50}$ is an indicator for depression at age 50, and the other variables are the same as defined above.

The hypothesis is that, even conditional on the initial characteristics described, sequences containing primarily traditional work with little interruption will be associated with higher retirement income and a lower incidence of depression at age 62. The next-best sequence will occur where nontraditional work is used sparingly as a stopgap, followed by long spells of nontraditional work. The sequences with the worst outcomes – i.e., lowest retirement income or highest incidence of depression – will be those associated with long spells of nontraditional work – in other words, weak attachment to the labor force – or very early retirement. This hypothesis means that relative to the base sequence of consistent traditional work, the coefficients γ_j will be increasingly negative for the retirement income median regressions, and increasingly positive for the depression probit regressions as they move from mostly traditional work to mostly nontraditional work and finally to unattached.

Results

This section first presents the results of the sequence analysis, before turning to the regression results.

²³ In practice, eight health conditions and five limitations to activities of daily living are used: The health conditions are: 1) high blood pressure with medication; 2) diabetes with insulin; 3) cancer of any kind, seeing doctor; 4) activity limiting lung disease; 5) heart condition, taking medication; 6) emotional/psychological problems; 7) stroke with problems afterward; and 8) arthritis with medication. The limitations to activities of daily living involve needing help with: 1) bathing; 2) getting dressed; 3) eating; 4) using a map; and 5) walking.

Sequence Analysis

The results show late-career employment patterns of HRS workers and how nontraditional jobs fit into those patterns. The sequence groupings were calculated for each definition of nontraditional work, the broad no-benefits definition and the narrower definition that includes both no-benefits and instability.

With the broad no-benefits definition of nontraditional work, five work patterns emerge (see Figure 4). The first two involve individuals who do not work consistently throughout their 50s and 60s. These individuals are either in an “Early Retirement” sequence with retirement in their 50s (21 percent of sample members) or are in a “Weak Attachment” sequence, with frequent spells of not working despite not retiring (16 percent). The next three sequences consist of people who work most of the time, and include sequences of work that are: “Mostly Nontraditional” (11 percent); “Mostly Traditional” (26 percent); and “All Traditional” (26 percent). The “ideal” employment pattern of working throughout one’s 50s and early 60s in a job with benefits is rare – less than a third of workers do it. Although somewhat surprising, the result does not seem to be an artifact of the HRS data used here; individuals in the *Panel Study of Income Dynamics* (PSID) from 1998-2010 showed almost the same low share of workers fitting the ideal pattern.²⁴

With respect to how nontraditional jobs are used within those sequences, it turns out that the vast majority of nontraditional work is done by those who do it often – it is used less often as a bridge to retirement or a stopgap to unemployment. To illustrate, Table 3 shows the distribution of nontraditional jobs across these sequence groups – under the broad definition, 16.9 percent of all jobs are nontraditional. The table shows that 53.7 percent of all nontraditional jobs (9.1/16.9) are within the Mostly Nontraditional sequence. The comparable number is 11.0 and 25.7 percent for both the Early Retirement and Weak Attachment sequences, representing a total of 36.7 percent of all nontraditional jobs. The remaining 9.6 percent of nontraditional jobs fit into the Mainly Traditional sequence. Overall, older workers tend to fall into two very different groups: they use these jobs either often or only briefly.

²⁴ In that dataset, both retirement plans and health insurance were identified for a sample of 403 individuals ages 50-52 in 1998 (the same start wave as the War Baby Cohort in the HRS), who worked at least once, and who were observed continuously through 2010. In this sample, only 24.6 percent worked in a traditional job the entire time – remarkably similar to the number in the HRS. It seems that it really is not that common to be in a consistent, traditional job between ages 50 and 62.

Turning to the more narrow definition of nontraditional work (see Figure 5) – jobs with no benefits and less stability – the fundamental nature of the sequence groupings is unchanged, although a sixth group differentiates very early retirements from those who simply retire prior to age 62.²⁵ The main difference between the two definitions is intuitive – sequences involving nontraditional work are less common. Table 3 shows that the majority of nontraditional jobs are done by the small percentage of workers in the Mostly Nontraditional sequence, who use nontraditional jobs consistently throughout their 50s and 60s. And within the group doing mostly traditional jobs, fewer spells of nontraditional work exist under the narrow definition.

Tables 4 and 5. Respectively, highlight the demographics of older workers, by sequence group, at their first HRS observation, based on the broad and narrow definitions of nontraditional work. Since most nontraditional jobs are held by people who do them frequently, the focus is on this sequence group. This group appears more vulnerable than workers who are mostly in more traditional work arrangements, although the differences are not as extreme as one might expect given their continued work in jobs without benefits. For example, those who are in the Mostly Nontraditional sequence are 77 percent white, compared to 81 percent for those in the Mostly Traditional sequence. Similarly, 47 percent of those in the Mostly Nontraditional sequence have at least some college education, compared to 57 percent in the Mostly Traditional sequence. The share who are female, the marriage rates, and the number of health conditions are fairly similar between the two groups. Table 5 shows a similar conclusion when the narrower definition of nontraditional work is used.

It would be nice to understand why some people spend most of their late work lives in nontraditional jobs. Latent Class Analysis (LCA), which identifies unobservable subgroups within a population (See Box 1), shows that workers who spend most of their time in nontraditional work fall into three basic categories (see Table 6).²⁶ The first group is defined by a lack of education: 15.4 percent of the Mostly Nontraditional sample lacks a high school degree.

²⁵ The five-group cluster analysis result for the narrow definition of nontraditional work grouped together older workers who do not consistently work with those who are in nontraditional work all of the time. The six-group cluster analysis result separated this combined grouping.

²⁶ Three groups were chosen because the Bayesian Information Criterion (BIC) was lower for three groups than for either two or four groups. An LCA analysis was also conducted for the more narrow definition of nontraditional work and is available upon request. Overall, the results were similar, with one group composed disproportionately of high school dropouts, the second of individuals in dual-earner relationships, and the third of individuals without an earning spouse. The main differences were that, under the narrow definition, the less-educated group included some high school graduates and the group without an earning spouse included no married individuals at all.

The second is defined by their marital status: the 35.5 percent of workers in this sequence are married and have an earning spouse. For these two groups, working in mostly nontraditional jobs makes sense. The less educated group likely has trouble finding good work, and the group with an earning spouse likely has much less need to hold a job with benefits. It is not as clear why a third group ends up in nontraditional work. This group is defined by not having an earning spouse, but otherwise appears fairly similar to the typical worker – albeit more likely to be non-white, slightly less educated, and slightly less healthy. Future work should investigate how workers who appear to be demographically similar end up in different work patterns in their early careers, but this question is beyond the scope of the current paper.

Box 1. Description of Latent Class Analysis

Latent class analysis (LCA) is a tool that allows researchers to identify relationships among observed categorical variables as a function of some unobserved grouping. The analysis starts with the observation that within the population, the observed variables are not independent. For example, within the group of workers in the Mostly Nontraditional group, being a high school dropout may tend to occur together with being nonwhite. The goal of latent class analysis is to group the observations so that within each group, or “latent class,” the observed categorical variables are locally independent. That is, being a high school dropout and nonwhite are both explained by some unobserved third variable, for example the level of economic advantage.

Conditional on an assumed number of classes, LCA outputs two sets of estimates: 1) the share of the population within each class; and 2) the conditional probabilities of having a given value for each observed variable within each class. These parameters are estimated by Maximum Likelihood Estimation. The second output – the conditional probabilities – have a special interpretation within LCA since they represent an association between the class and the observed characteristic. That is, if one class is comprised disproportionately of high school dropouts who are nonwhite, then that class can be viewed as more economically disadvantaged than the other.

Regression Results

The regression results for retirement income are presented in Tables 7a (broad definition) and 7b (narrow definition) and for depression in Tables 8a and 8b. In each table, four sensitivities are shown: 1) only sequence groupings (and year dummies) as independent variables; 2) adding demographics and initial health; 3) adding pension coverage; and 4) adding lifetime income or initial depression. Showing the regressions in this manner illustrates how much of the raw relationship between the sequence and the outcome of interest is explained away by the added factors.

Looking first at retirement income, under the broad definition of nontraditional work (Table 7a) each sequence shown is associated with lower median retirement income than the base case (which is those in traditional jobs their entire late career). Focusing on those consistently in nontraditional jobs – the way in which most nontraditional jobs are used – this difference is nearly 28 percent. Moving to the second column, little of this difference is explained by demographics alone, as the coefficient remains at negative 26 percent even after these controls are introduced. Instead, much – but not all – of the difference is due to the availability of pensions and high lifetime income prior to late career; the coefficient drops to negative 7.7 percent by the time both these factors are introduced. The decline in the coefficient suggests much of the negative relationship between having a late-career work history defined by nontraditional work and retirement income is due to things that happened prior – perhaps an entire career of non-traditional work. Still, the fact that the coefficient remains significant (at least at the 10-percent level) suggests that spending a majority of one’s late career in nontraditional work likely does lower retirement income. The other coefficients in the regression are largely intuitive, with more education and marriage being associated with more retirement income and minority status and poor initial health with less.

Moving to the narrow definition of nontraditional work (Table 7b), the overall interpretation of the results is similar. Perhaps the most notable difference is that, because the coefficient on the mainly nontraditional sequence starts out smaller initially, by the time all controls are introduced the result (negative 6.6 percent) is no longer statistically significant. The other coefficients are again intuitive.

Turning to a more holistic measure of well-being – depression – the results under the broad definition (Table 8a) suggest that those in nontraditional jobs frequently are significantly more likely to be depressed than those consistently in traditional work. Furthermore, the effect is largely invariant to the controls added, with the sequence associated with a 5.9-percent increase in depression at 62 without controls and a 5.0-percent increase with the complete set of controls. Unlike in the case of retirement income, going to the narrow definition of nontraditional work (Table 8b) does not affect the interpretation of the depression regression much – in the specification with full controls, being in the mostly nontraditional sequence is associated with a 4.8-percent increase in the likelihood of depression. Again, the other coefficients are largely intuitive.

Conclusion

Despite the increased focus on nontraditional jobs in the popular press and academic literature, how older workers use these jobs and their effect on how well older workers are prepared for retirement has not been studied. Yet, working consistently in a job with benefits throughout one's 50s and early 60s is likely key to retirement preparedness. This paper uses sequence analysis to characterize how older workers use nontraditional jobs in their late careers and then regression analysis to see how these patterns relate to their available retirement income.

The results suggest that a third or less of workers have the "ideal" sequence of late-career employment: a traditional job with benefits consistently from ages 50-62. Many retire early or have brief bouts of not working or nontraditional work and, worse, many have a weak attachment to the labor force or are in nontraditional jobs consistently. The regression results show that being employed frequently in nontraditional work during one's late career is associated with both lower retirement income and higher rates of depression. Furthermore, these differences remain even when controlling for lifetime income or depression prior to age 50 (with the exception of retirement income under the narrow definition), suggesting late-career nontraditional work is at least partially the culprit. This finding illustrates the importance of attempting to expand benefits to these workers – for example through programs like state-level auto-IRAs.

References

- Aisenbrey, Silke and Anette E. Fasang. 2010. "New Life for Old Ideas: The 'Second Wave' of Sequence Analysis Bring the 'Course' Back into the Life Course." *Sociological Methods & Research* 38(3): 420-462.
- Barbieri, Paolo and Stefani Scherer. 2009. "Labour Market Flexibilization and its Consequences in Italy." *European Sociological Review* 25(5): 677-692.
- Cahill, Kevin E., Michael D. Giandrea, and Joseph F. Quinn. 2011. "How Does Occupational Status Impact Bridge Job Prevalence?" Working Paper 447. Washington, DC: U.S Bureau of Labor Statistics.
- Calvo, Esteban, Ignacio Madero-Cabib, and Ursula M. Staudinger. 2017. "Retirement Sequences of Older Americans: Moderately De-Standardized and Highly Stratified across Gender, Class, and Race." *The Gerontologist* 58(6): 116-1176.
- Collins, Brett, Andrew Garin, Emilie Jackson, Dmitri Koustas, and Mark Payne. 2019. Is Gig Work Replacing Traditional Employment? Evidence from Two Decades of Tax Returns. Statistics of Income Working Paper. Washington, DC: Internal Revenue Service.
- Cornwell, Benjamin. 2015. *Social Sequence Analysis Methods and Applications*. New York, NY: Cambridge University Press.
- Farrell, Diana and Fiona Grieg. 2016. "The Online Platform Economy: Has Growth Peaked?" New York, NY: JP Morgan Chase & Co. Institute.
- Fournier, Geneviève, Hélène Zimmermann, and Christine Gauthier. 2011. "Instable Career Paths Among Workers 45 and Over: Insight Gained from Long-Term Career Trajectories." *Journal of Aging Studies* 25(3): 316-327.
- Fuller, Sylvia and Natasha Stecy-Hildebrandt. 2015. "Career Pathways for Temporary Workers: Exploring Heterogeneous Mobility Dynamics with Sequence Analysis." *Social Science Research* 50: 76-99.
- Gustman, Alan L. and Thomas L. Steinmeier. 2000. "Retirement Outcomes in the Health and Retirement Study." *Social Security Bulletin* 63(4): 57-71.
- Halpin, Brendan. 2013. "Imputing Sequence Data: Extensions to Initial and Terminal Gaps, Stat's *mi*." Working Paper 2013-01. Limerick, Ireland: University of Limerick Department of Sociology.
- Hollister, Matissa. 2009. "Is Optimal Matching Suboptimal?" *Sociological Methods & Research* 38(2): 235-264.

- James, Jacquelyn B., Jennifer E. Swanberg, and Sharon P. Mckechnie. 2007. "Responsive Workplaces for Older Workers: Job Quality, Flexibility and Employee Engagement." *Issue Brief 11*. Chestnut Hill, MA: Sloan Center on Aging and Work at Boston College.
- Johnson, Richard W. and Janette Kawachi. 2007. "Job Changes at Older Ages: Effects on Wages, Benefits and Other Job Attributes." Working Paper 2007-4. Chestnut Hill, MA: Center for Retirement Research at Boston College.
- Katz, Lawrence F. and Alan B. Krueger. 2016. "The Rise and Nature of Alternative Work Arrangements in the United States, 1995-2015." Working Paper. Princeton, NJ: Princeton University.
- Katz, Lawrence F. and Alan B. Krueger. 2019. "Understanding Trends in Alternative Work Arrangements in the United States." Working Paper 25425. Cambridge, MA: National Bureau of Economic Research.
- MacIndoe, Heather and Andrew Abbott. 2011. "Sequence Analysis and Optimal Matching Techniques for Social Science Data." In *Handbook of Data Analysis*, edited by Melissa Hardy and Alan Bryman, 387-406. London, UK: SAGE Publications LTD.
- Quinn, Joseph and Richard Burkhauser. 1990. "Work and Retirement," in *Handbook of Aging and the Social Sciences* (3rd edition), edited by Robert Binstock and Linda George. San Diego, CA: Academic Press.
- Ruhm, Christopher J. 1990. "Bridge Jobs and Partial Retirement." *Journal of Labor Economics* 8(4): 482-501.
- U.S. Bureau of Labor Statistics. 2018. "Contingent and Alternative Work Arrangements." Washington, D.C.
- U.S. Government Accountability Office. 2015. Contingent Workforce. GAO-15-168R. Washington, D.C.: U.S. Government Accountability Office.

Table 1. *Sample Restrictions*

Restriction	Sample
Total HRS sample	37,495
Born from 1939 to 1954 and observed at 52	11,732
Live to age 62	10,940
Not dropped by the HRS	10,097
Report working with income	8,513
Have less than three missing observations	5,030
Work at least once between ages 50 and 62	4,174

Source: Authors' calculations from *Health and Retirement Study* (1992-2016).

Table 2. *Select Characteristics of Workers in Nontraditional Jobs, 2017*

	“Alternative” BLS	No benefits minus BLS
Average tenure	11 years	6 years
<i>Household income</i>		
10th percentile	\$22,500	\$17,500
25th percentile	45,000	32,500
Median	67,500	55,000
<i>Demographics</i>		
At least some college	65%	52%
Non-white	20	34

Note: The “no benefits minus BLS” column consists of those workers without benefits who are not already captured under the BLS definition.

Source: Authors' calculations from *Current Population Survey May Supplement* (2017).

Table 3. *Share of Jobs that are Nontraditional and in Each Sequence Group*

Sequence group	Nontraditional jobs			
	No benefits	Distribution of no benefits jobs	No benefits and instable	Distribution of no benefits and instable jobs
Very early retirement	-		0.5%	6.4%
Early retirement	1.9%	11.0%	3.6	17.9
Weak attachment	4.3	25.7	1.4	47.3
Mostly nontraditional	9.1	53.7	0.7	9.2
Mostly traditional	1.6	9.6	1.4	19.1
Traditional	0.0	0	0	0.0
Total	16.9	100	7.6	100

Source: Authors' calculations from *Health and Retirement Study* (1992-2016).

Table 4. *Older Workers' Demographics for Benefits Only Definition of Nontraditional Work*

Demographics at ages 50-52	Sequence group				
	Early retirement	Weak attachment	Mostly nontraditional	Mostly traditional	All traditional
<i>Share of total sample</i>	21%	16%	11%	26%	26%
Female	62	65	55	55	52
<i>Race</i>					
White	78	76	77	81	84
Black	17	15	15	13	11
Other	4	9	9	5	5
<i>Education</i>					
Less than high school	16	19	15	9	6
High school	38	34	38	34	29
Some college	24	23	26	29	26
College	22	24	21	28	39
Coupled	82	81	76	81	82
<i>Has pension wealth</i>					
DB pension	32	20	13	32	29
DC pension	26	20	12	27	33
Number of health conditions	1.0	0.8	0.7	0.7	0.6
Household size	2	3	2	3	3
Number of Children	3	3	3	3	2
Median wages	\$35,796	\$24,423	\$17,898	\$43,135	\$58,396
<i>Median wealth</i>					
Financial	\$15,488	\$11,051	\$9,127	\$17,898	\$21,477
Housing	\$93,052	\$80,540	\$70,530	\$81,088	\$93,052

Notes: Wages and wealth are in 2018 dollars. AIME is an individual's Average Indexed Monthly Earnings based on a linkage to Social Security Administrative data summarized by RAND in its version of the HRS.

Source: Authors' calculations from *Health and Retirement Study* (1992-2016).

Table 5. *Older Workers' Demographics for Nontraditional Work with No Benefits and Unstable Hours Definition of Nontraditional Work*

Demographics at ages 50-52	Sequence group					
	Very early retirement	Early retirement	Weak attachment	Mostly nontraditional	Mostly traditional	Traditional
<i>Share of total sample</i>	7%	21%	9%	5%	26%	32%
Female	61	59	76	51	55	52
<i>Race</i>						
White	77	78	75	83	80	83
Black	17	17	16	10	13	12
Other	5	6	9	6	6	5
<i>Education</i>						
Less than high school	21	11	27	9	10	7
High school	37	36	38	29	34	31
Some college	22	25	21	30	29	26
College	19	28	14	32	27	35
Married	57	57	51	44	52	48
<i>Has pension wealth</i>						
DB pension	29	36	8	15	28	27
DC pension	20	31	8	12	25	30
Number of health conditions	1.2	0.9	1.0	0.6	0.7	0.6
Household size	3	3	3	2	3	3
Number of children	3	3	3	2.5	3	2
Median wages	\$37,576	\$52,019	\$16,636	\$30,327	\$47,245	\$54,462
<i>Median wealth</i>						
Financial	94,580	67,700	57,429	100,186	82,313	73,381
Housing	114,578	119,172	108,269	149,815	108,051	123,842

Note: Wages and wealth are in 2018 dollars.

Source: Authors' calculations from *Health and Retirement Study* (1992-2016).

Table 6. *LCA Analysis of Mostly Nontraditional Sequence Group*

	High school dropouts	Married with an earning spouse	Solo earners
Share of "mostly nontraditional" sequence	15.4%	35.5%	49.1%
Female	53.7	60.4	52.1
Non-white	44.8	16.9	22.1
<i>Education</i>			
High school dropouts	100.0	0.6	0.0
High school graduates	0.0	39.6	47.9
Some college	0.0	33.8	28.2
College graduate	0.0	26.0	23.9
<i>Marriage status</i>			
Married	80.4	100.0	40.4
Married with an earning spouse	32.8	94.2	0.0
<i>Employer-sponsored plans from past job</i>			
Defined benefit	0.0	31.2	8.4
Defined contribution	7.5	24.7	7.5
<i>Other limiting factors</i>			
Own health limits work	18.5	5.8	13.2
Caregiving for someone with ADL/IADL	9.6	12.9	17.9

Source: Authors' calculations from *Health and Retirement Study* (1992-2016).

Table 7a. *Effect of Select Variables on Median Retirement Income, No Benefits Definition*

	Specification			
	(1)	(2)	(3)	(4)
<i>Sequence (Traditional = base case)</i>				
Mostly traditional	-0.0730*** (0.0265)	-0.0553* (0.0326)	-0.0299 (0.0325)	-0.0305 (0.0312)
Mostly nontraditional	-0.2783*** (0.0357)	-0.2623*** (0.0440)	-0.1682*** (0.0454)	-0.0774* (0.0437)
Weak attachment	-0.1497*** (0.0305)	-0.1459*** (0.0370)	-0.0864** (0.0379)	-0.0377 (0.0363)
Early retirement	-0.1131*** (0.0284)	-0.0171 (0.0343)	-0.0134 (0.0344)	0.0114 (0.0330)
<i>Other controls</i>				
Black		-0.1592*** (0.0338)	-0.1617*** (0.0336)	-0.1112*** (0.0324)
Other non-white		-0.2404*** (0.0593)	-0.2091*** (0.0590)	-0.0648 (0.0567)
Female		0.0689*** (0.0254)	0.0883*** (0.0254)	0.0458* (0.0243)
Some college		0.2082*** (0.0282)	0.1997*** (0.0282)	0.1205*** (0.0271)
College degree		0.4335*** (0.0291)	0.3926*** (0.0293)	0.2765*** (0.0284)
Married		0.4655*** (0.0320)	0.4794*** (0.0319)	0.1518*** (0.0329)
Number of initial health conditions		-0.0710*** (0.0129)	-0.0694*** (0.0128)	-0.0472*** (0.0123)
Retirement plan at age 50			0.1759*** (0.0261)	0.0452* (0.0255)
Average Indexed Monthly Earnings at age 50				0.3626*** (0.0162)
Start wave dummies included?	Yes	Yes	Yes	Yes
Number of observations	3,219	2,287	2,287	2,262
Pseudo R-squared	0.030	0.174	0.184	0.282

Notes: Regression is a quintile regression at the median. Standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Source: Authors' calculations from the *Health and Retirement Study* (1992-2016).

Table 7b. *Effect of Select Variables on Median Retirement Income, No Benefits with Instability*
Definition of Nontraditional Work

	Specification			
	(1)	(2)	(3)	(4)
<i>Sequence (Traditional = base case)</i>				
Mostly traditional	-0.0904*** (0.0272)	-0.0818** (0.0331)	-0.0709** (0.0314)	-0.0466 (0.0285)
Mostly nontraditional	-0.1526*** (0.0535)	-0.1723** (0.0669)	-0.0835 (0.0639)	-0.0513 (0.0584)
Weak attachment	-0.3102*** (0.0392)	-0.2417*** (0.0489)	-0.1680*** (0.0478)	-0.0565 (0.0439)
Early retirement	-0.0168 (0.0288)	-0.0015 (0.0344)	-0.0115 (0.0325)	-0.0076 (0.0296)
Very early retirement	-0.1566*** (0.0418)	-0.0604 (0.0503)	-0.0365 (0.0477)	0.0155 (0.0437)
<i>Other controls</i>				
Black		-0.1637*** (0.0365)	-0.1479*** (0.0345)	-0.1199*** (0.0315)
Other non-white		-0.2148*** (0.0635)	-0.2143*** (0.0600)	-0.0860 (0.0548)
Female		0.0739*** (0.0274)	0.0902*** (0.0261)	0.0527** (0.0237)
Some college		0.2015*** (0.0304)	0.1946*** (0.0289)	0.1057*** (0.0264)
College degree		0.4438*** (0.0313)	0.3990*** (0.0300)	0.2618*** (0.0276)
Married		0.4630*** (0.0345)	0.4696*** (0.0326)	0.1540*** (0.0321)
Number of initial health conditions		-0.0618*** (0.0140)	-0.0695*** (0.0132)	-0.0495*** (0.0120)
Retirement plan at age 50			0.1795*** (0.0265)	0.0625** (0.0246)
Average Indexed Monthly Earnings at age 50				0.3712*** (0.0158)
Start wave dummies included?	Yes	Yes	Yes	Yes
Number of observations	3,219	2,288	2,288	2,263
Pseudo R-squared	0.030	0.171	0.184	0.282

Notes: Regression is a quintile regression at the median. Standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Source: Authors' calculations from the *Health and Retirement Study* (1992-2016).

Table 8a. *Effect of Select Variables on Likelihood of Depression at Age 62, No Benefits Definition*

	Specification			
	(1)	(2)	(3)	(4)
<i>Sequence (Traditional = base case)</i>				
Mostly traditional	0.0340*	0.0279*	0.0263*	-0.0017
	(0.0174)	(0.0146)	(0.0146)	(0.0093)
Mostly nontraditional	0.0591**	0.0431**	0.0350*	0.0504***
	(0.0245)	(0.0198)	(0.0199)	(0.0144)
Weak attachment	0.0884***	0.0520***	0.0462***	0.0211*
	(0.0225)	(0.0173)	(0.0175)	(0.0114)
Early retirement	0.1184***	0.0618***	0.0585***	0.0616***
	(0.0222)	(0.0166)	(0.0166)	(0.0117)
<i>Other controls</i>				
Black		0.0112	0.0111	-0.0111
		(0.0122)	(0.0122)	(0.0080)
Other non-white		0.0495**	0.0500**	0.0897***
		(0.0216)	(0.0216)	(0.0161)
Female		0.0159*	0.0146	0.0158**
		(0.0096)	(0.0096)	(0.0072)
Some college		-0.0248***	-0.0237***	-0.0001
		(0.0087)	(0.0088)	(0.0068)
College degree		-0.0576***	-0.0557***	-0.0351***
		(0.0077)	(0.0079)	(0.0062)
Married		-0.0208**	-0.0210**	-0.0212***
		(0.0090)	(0.0090)	(0.0061)
Number of initial health conditions		0.0414***	0.0413***	0.0297***
		(0.0042)	(0.0042)	(0.0029)
Retirement plan at age 50			-0.0131	-0.0170***
			(0.0089)	(0.0060)
Depression at age 50				0.1638***
				(0.0134)
Start wave dummies included?	Yes	Yes	Yes	Yes
Number of observations	3,909	2,870	2,870	1,761
Pseudo R-squared	0.027	0.072	0.073	0.131

Notes: Table shows the average marginal effect on the probability of depression for each variable. Standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Source: Authors' calculations from the *Health and Retirement Study* (1992-2016).

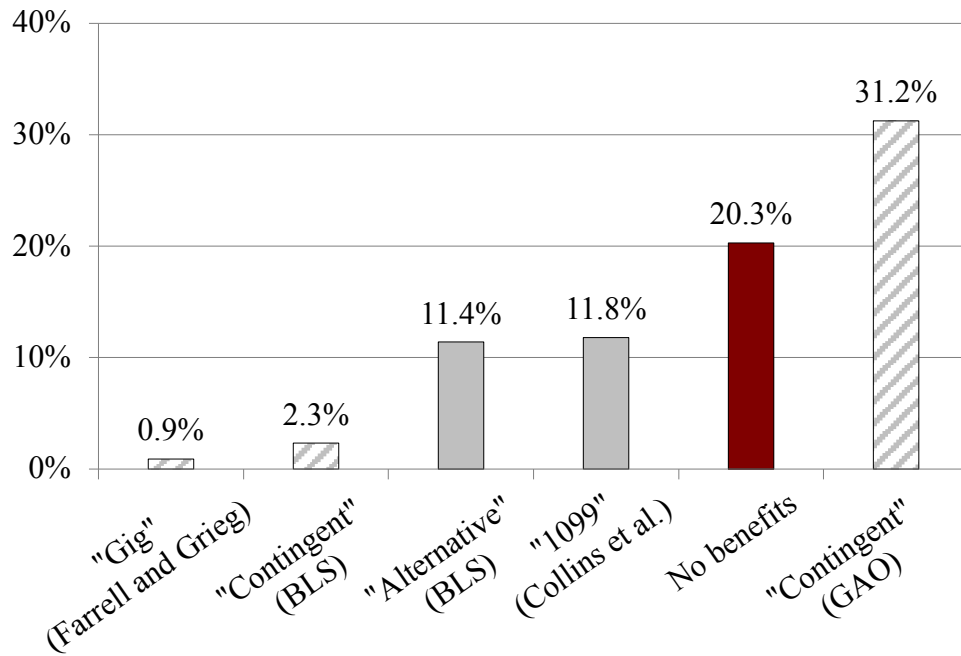
Table 8b. *Effect of Select Variables on Likelihood of Depression at Age 62, No Benefits with Instability Definition of Nontraditional Work*

	Specification			
	(1)	(2)	(3)	(4)
<i>Sequence (Traditional = base case)</i>				
Mostly traditional	0.0489*** (0.0170)	0.0332** (0.0136)	0.0317** (0.0136)	0.0224** (0.0098)
Mostly nontraditional	0.0469 (0.0319)	0.0338 (0.0259)	0.0283 (0.0256)	0.0483*** (0.0185)
Weak attachment	0.1620*** (0.0298)	0.0958*** (0.0225)	0.0881*** (0.0229)	0.0577*** (0.0153)
Early retirement	0.0723*** (0.0189)	0.0435*** (0.0144)	0.0433*** (0.0143)	0.0500*** (0.0106)
Very early retirement	0.1263*** (0.0305)	0.0303 (0.0201)	0.0275 (0.0199)	0.0712*** (0.0166)
<i>Other controls</i>				
Black		0.0106 (0.0122)	0.0105 (0.0122)	-0.0094 (0.0081)
Other non-white		0.0456** (0.0211)	0.0456** (0.0210)	0.0798*** (0.0155)
Female		0.0133 (0.0096)	0.0121 (0.0096)	0.0165** (0.0073)
Some college		-0.0239*** (0.0087)	-0.0228*** (0.0088)	-0.0005 (0.0069)
College degree		-0.0567*** (0.0077)	-0.0549*** (0.0080)	-0.0357*** (0.0061)
Married		-0.0240** (0.0102)	-0.0241** (0.0102)	-0.0253*** (0.0072)
Number of initial health conditions		0.0420*** (0.0042)	0.0419*** (0.0042)	0.0298*** (0.0030)
Retirement plan at age 50			-0.0116 (0.0089)	-0.0188*** (0.0060)
Depression at age 50				0.1657*** (0.0135)
Start wave dummies included?	Yes	Yes	Yes	Yes
Number of observations	3,909	2,871	2,871	1,762
Pseudo R-squared	0.029	0.074	0.074	0.127

Notes: Table shows the average marginal effect on the probability of depression for each variable. Standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Source: Authors' calculations from the *Health and Retirement Study* (1992-2016).

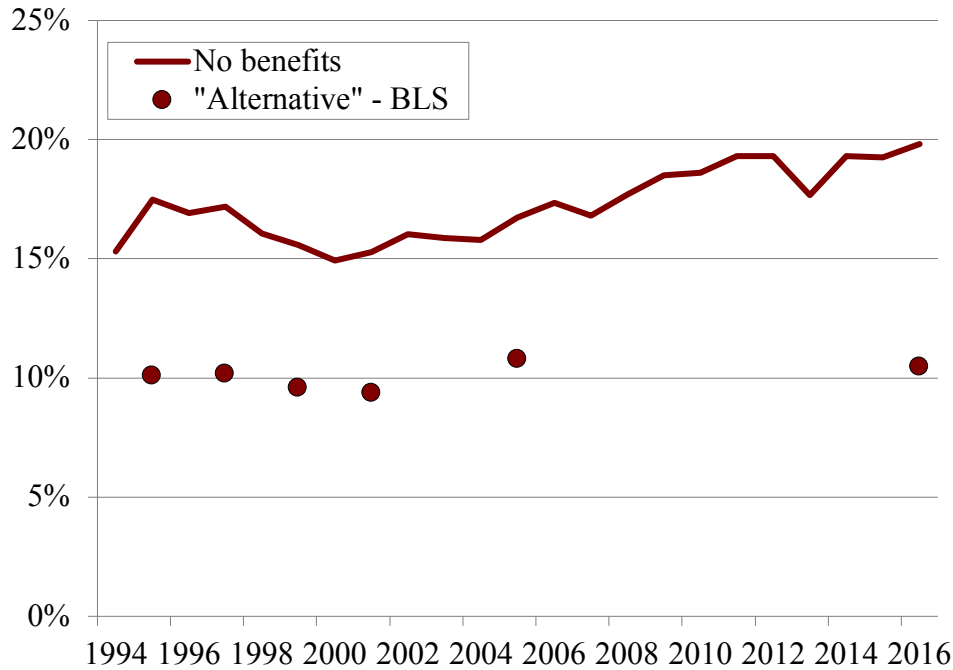
Figure 1. *Percentage of Workers Ages 50-62 in Nontraditional Jobs by Definition*



Notes: "Gig" definition as in Ferrell and Grieg (2016) and covers all workers. "1099" workers defined as in Collins et al. (2019) and applies to all workers. "Contingent" (BLS), "Alternative" (BLS), "No benefits," and "Contingent" (GAO) were calculated by the authors and apply to workers age 50-62.

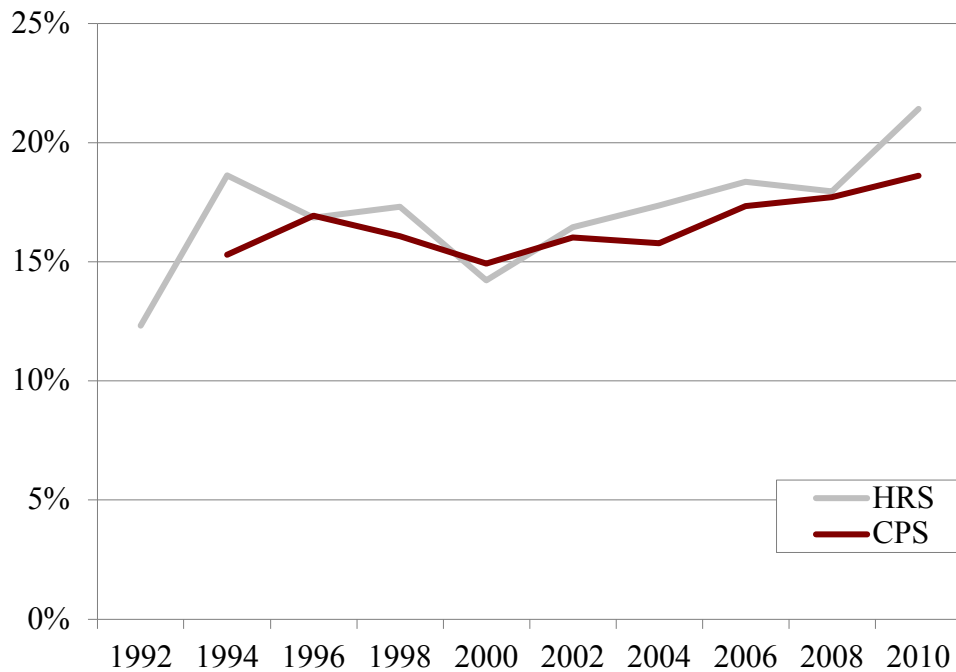
Sources: Ferrell and Grieg (2016); Collins et al. (2019); and *Current Population Survey May Supplement* (2017).

Figure 2. *Percentage of Workers in Nontraditional Jobs under Different Definitions, 1994-2016*



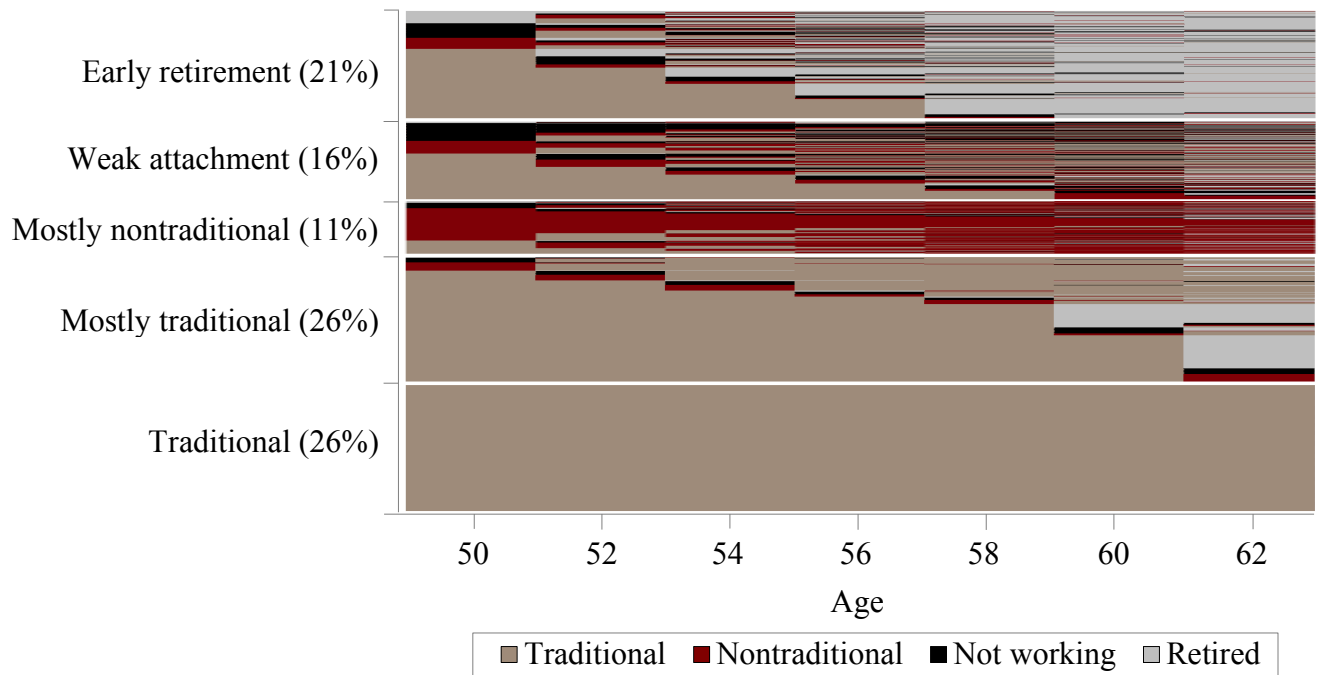
Note: “Alternative” estimate comes from Katz and Krueger (2019) and includes *all* workers.
 Sources: *Current Population Survey March Supplement* (1995-2017); and Katz and Krueger (2019).

Figure 3. *Percentage of Workers Ages 50-62 in Jobs with No Benefits by Dataset, 1992-2010*



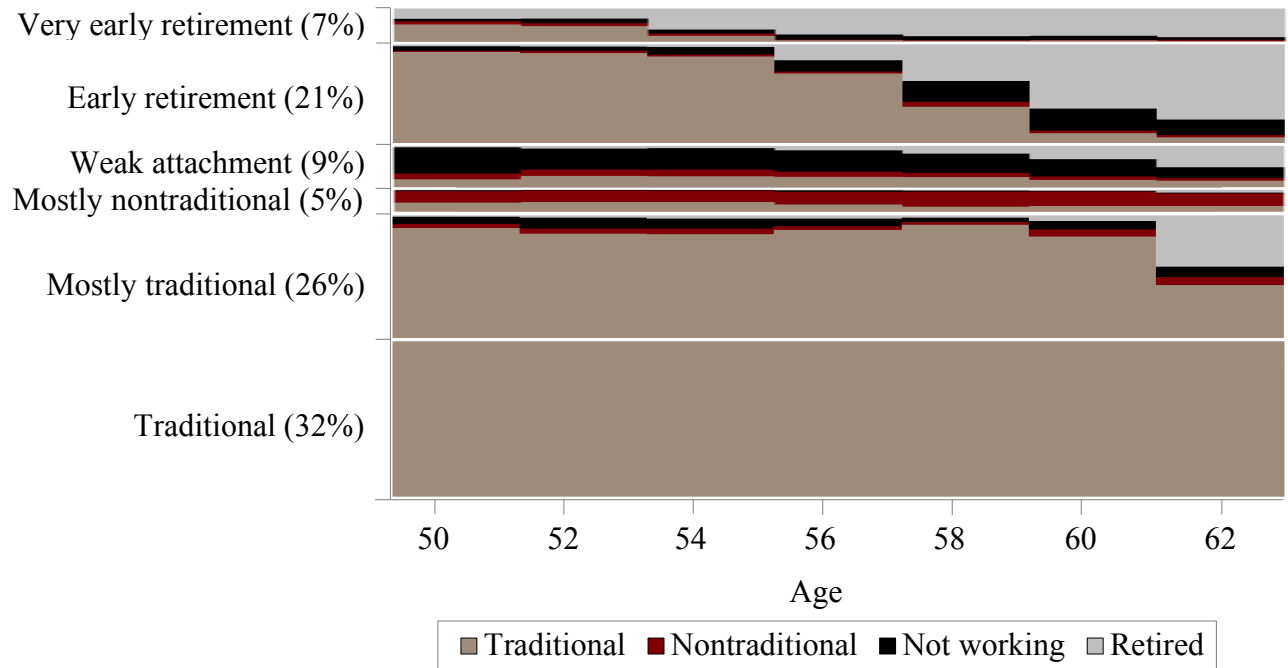
Sources: Authors’ calculations from *Health and Retirement Study* (1992-2010); and *Current Population Survey March Supplement* (1995-2011).

Figure 4. *Work Histories from Ages 50-62, No Benefits Definition of Nontraditional Work*



Source: Authors' calculations using *Health and Retirement Study* (1992-2016).

Figure 5. *Work Histories from Ages 50-62, No Benefits with Instability Definition of Nontraditional Work*



Source: Authors' calculations using *Health and Retirement Study* (1992-2016).

RECENT WORKING PAPERS FROM THE
CENTER FOR RETIREMENT RESEARCH AT BOSTON COLLEGE

Will More Workers Have Nontraditional Jobs as Globalization and Automation Spread?

Matthew S. Rutledge, Gal Wettstein, and Sara Ellen King, July 2019

Do States Adjust Medicaid Enrollment in Response to Capitation Rates? Evidence from the Medicare Part D Clawback

Laura D. Quinby and Gal Wettstein, June 2019

The Effect of Medicare Part D on Evergreening, Generic Entry, and Drug Prices

Geoffrey T. Sanzenbacher and Gal Wettstein, May 2019

Is the Drop in Fertility Due to The Great Recession or a Permanent Change?

Alicia H. Munnell, Anqi Chen, and Geoffrey T. Sanzenbacher, March 2019

Will Fewer Children Boost Demand for Formal Caregiving?

Gal Wettstein and Alice Zulkarnain, March 2019

The Relationship Between Occupational Requirements and SSDI Activity

Matthew S. Rutledge, Alice Zulkarnain, and Sara Ellen King, February 2019

How Does Contingent Work Affect SSDI Benefits?

Matthew S. Rutledge, Alice Zulkarnain, and Sara Ellen King, February 2019

Do Pension Cuts for Current Employees Increase Separation?

Laura D. Quinby and Gal Wettstein, January 2019

Competition, Asymmetric Information, and the Annuity Puzzle: Evidence from a Government-Run Exchange in Chile

Gastón Illanes and Manisha Padi, January 2019

Failure to Contribute: An Estimate of the Consequences of Non- and Underpayment of Self-Employment Taxes by Independent Contractors and On-Demand Workers on Social Security

Caroline Bruckner and Thomas L. Hungerford, January 2019

How Much Income Do Retirees Actually Have? Evaluating the Evidence from Five National Datasets

Anqi Chen, Alicia H. Munnell, and Geoffrey T. Sanzenbacher, November 2018

All working papers are available on the Center for Retirement Research website (<https://crr.bc.edu>) and can be requested by e-mail (crr@bc.edu) or phone (617-552-1762).