Impacts of Workforce Training on School-Work Sequences in a Randomized Controlled Trial

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Abstract

This paper introduces a promising approach for analyzing the impacts of workforce training on whole sequences of school and work activities. Originating in DNA research, sequence analysis with Optimum Matching is the basis for a rapidly growing social science literature but until now has not been applied in workforce program evaluations. Using data from a randomized controlled trial of Year Up, a leading training program for young adults, we find that the 2,544 sample members followed eight distinct school-work sequence patterns over a three-year follow-up period. The program increased the likelihood of sequences characterized by movement from full-time training to higher-wage jobs and decreased the likelihood of sequences leading to low-wage and part-time work. Year Up had little effect on the likelihood of sustained school enrollment or persistent disconnection from school and work. Baseline characteristics predicted sequence type in ways generally consistent with the basic research literature. Further bolstering their validity, three-year sequence types also were strongly associated with a series of six-year outcomes.

Keywords

Career pathways
Sequence analysis
Randomized controlled trial
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Workforce training

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Introduction

As career opportunities have grown for young adults with college degrees in recent decades, prospects for those without postsecondary credentials have stagnated or declined (Binder and Bound, 2019; Carnevale et al., 2018; Escobari et al., 2019; Groshen and Holzer, 2019; Ross et al., 2018). Absent post-secondary education, young adulthood often begins with spells of unemployment and intermittent low-wage work (Millett and Kevelson, 2018) that frequently lead to long-term disconnection (Lewis and Gluskin, 2018; Millett and Kevelson, 2018). Concerns about the resulting individual and societal costs (Belfield et al., 2012) have stimulated a host of policies and programs seeking to create alternative career paths for young adults.

This paper addresses two knowledge gaps that have hampered such efforts. One gap is that, until recently, none of the approaches tested have substantially increased earnings in randomized controlled trials (RCTs)—the gold standard for impact evaluation (Fein and Hamadyk, 2018, pp. 5-7). A second gap has been the absence of measures summarizing whole career sequences in evaluations, which have continued to rely on traditional point-in-time and period measures of education and employment to discern career progress. Such outcomes are useful in reaching a bottom-line verdict on programs' effectiveness but afford little insight into how they alter individual career trajectories.

We use data from an RCT of Year Up—a national training program for young adults—to analyze impacts on career trajectories. For this evaluation, researchers randomly assigned 2,544 young adults to well-matched treatment (program) and control (business-as-usual) groups (Fein & Dastrup 2022). Unusually large and lasting increases in average earnings hint at important shifts in underlying sequences of school and work activities.

Analyzing impacts on whole sequences requires a method for standardizing and summarizing steps to support treatment-control comparisons across varying occupations. We show that sequence analysis with Optimum Matching (OM) methods provides a useful tool for such summarization. Sequence analysis originated in molecular biology as a tool for comparing DNA sequences (Sankoff and Kruskal, 1983), was introduced to the study of social phenomena in the 1980s (Abbott and Forrest, 1986) and since has been used in a wide variety of social scientific investigations (Cornwall, 2015; Ritschard and Studer, Eds., 2018). Cornwall (2015) provides a useful introduction to these methods.

As applied in this paper, sequence analysis involved four main steps: 1) establish each sample member's primary school-work activity in each of the first 36 months after random assignment; 2) create a summary measure of similarity for each possible pair of sequences in the sample, 3) apply cluster analysis to identify a limited number of groups with similar sequences, and 4) assess the relationships of treatment-control status and other factors to sequence group assignments.

For the first step, we assigned a primary school-work status to each individual in every month from seven possible activities: full-time school; full-time work at varying wage rates (<$15, $15-19, $20-24, and $25+); part-time school or work; and no school or work. Results from the next two steps showed that 36-month sequences clustered into eight distinct groups:

- Three clusters, observed mainly in the treatment group, involved transitions from full-time school (e.g., Year Up training) to jobs at varying wage levels above the $15/hour floor that Year Up targeted.
- Another three clusters—one involving full-time work at <$15/hour and two dominated by part-time school/work—were most common in the control group.
- The final two clusters--sustained full-time training and persistent disconnection from school and work—evidenced no treatment-control differences.

Last, we analyzed relationships between cluster assignments and other characteristics of sample members to validate and better understand the sequence patterns. A series of initial characteristics predicted young adults' subsequent sequence types in ways generally consistent with the basic research literature. In turn, the three-year sequence assignments: 1) predicted a set of outcomes measured six years after study intake, and 2) fully mediated Year Up's impacts on six-year outcomes.

To our knowledge, this paper is the first to use OM to study impacts on sequences in an RCT of a social program. In the paper's concluding section, we discuss how the findings have helped to understand one program's impacts and encourage wider application to other intervention studies.

2.1. Literature on career sequences in young adulthood

A summary of basic research on career sequences can help to set this paper's methods and findings in context. This section reviews the populations, school and work statuses, and antecedents and consequences of career sequences examined in studies to date.

The bulk of analyses of young adults' career sequences have used data on national samples of young adults. Most have focused on European populations (Anyadike-Danes and McVicar, 2005, 2010; Brzinsky-Fay, 2007; Dorsett and Lucchino, 2014; Guidici and Morselli, 2019; Lorentzen et al., 2019; Scherer, 2001; Schwanitz, 2017; Sirnio et al., 2017), although a few have included U.S. comparisons (Aisenbrey and Fasang, 2017; Quintini and Manfredi, 2009) or focused solely on U.S. samples (Kang 2019).

These studies typically use data from longitudinal surveys or national registration systems to analyze sequences of monthly or annual outcomes extending at least five years, often starting at the conclusion of secondary education. Most studies distinguish school, work, or neither activity as possible statuses, elaborating on these statuses (e.g., part-time/full-time, unemployed/not in the labor market) to varying degrees. The number of sequence types, or clusters, identified generally ranges from 5 to 15.

At the national level, the vast majority of young adults exhibit relatively smooth career patterns—transitioning from high school to post-secondary education to sustained full-time employment, with sub-clusters distinguishing varying durations of education. A minority of young adults – typically 10-15 percent of national samples – follow sequences marked by prolonged periods with intermittent or no labor market activity (i.e., school or work).

Most studies of career sequences in broad national samples have not sought to distinguish steps on career ladders within occupations. This gap reflects the difficulty of conceptualizing and creating comparable measures of steps in varied occupations. Investigations of progress in career pathways thus have tended to focus on specific occupations. Examples include studies of career pathways of chefs (Borkenhagen and Levi Martin, 2018), 18th century musicians (Abbott and Hrycak, 1990), and women financial executives (Blair-Loy, 1999).

A small number of studies have shown that proxies for job status can be used to capture career progress in analysis of sequences in broader populations. For example, Aisenbrey and Fasang (2017) use an index of occupational prestige (Treiman, 1977) to discern career progress among young adults in the U.S. and Germany. Joseph et al. (2012) distinguish nonmanagerial and managerial jobs in analyzing mobility within and across IT and non-IT sectors in the U.S. In this paper, we take a similar approach in assigning a proxy for job status to each employment spell but use a different measure for status—hourly wages.

Another limitation of the career sequence literature is scant attention to low-income populations. Broader population studies can establish the overall connection between poverty and career patterns but have not illuminated the varying paths that low-income young adults follow. A stronger grasp of these paths and associated factors is needed to identify young adults that interventions should target and the services that might be beneficial.

A brief summary of findings on correlates of sequences and related outcomes can help in establishing general expectations for results from this paper's predictive analyses. We include several recent studies that, though focused on more traditional career outcomes, provide useful evidence on predictors. These include Ross et al.'s (2018) analysis of factors predicting job quality at age 29 and two studies of correlates of disconnection among young adults (Millett and Kevelson, 2018; Tayfur et al., 2021). The Ross et al. study is, to our knowledge, the only one focused specifically on a low-income young adult population. We organize predictors into five groups, mirroring categories in Fein's (2012) heuristic framework for career pathways: basic demographic characteristics; education and skills; career orientation; resources and supports; and personal challenges and vulnerabilities.

Most studies have found persisting effects of *gender and race-ethnicity*, net of other factors. Compared to men, women's career sequences are less likely to be defined by long-term employment, with persisting spells of neither school nor work associated with parenting (Aisenbrey and Fasang, 2017; Dorsett and Lucchino, 2014; Klug et al., 2019; Quintini and Manfredi, 2009; Ross et al., 2018; Millett and Kevelson, 2018). Among race-ethnicity groups in the US, sequences dominated by sustained disconnection are more likely among Black men than other groups of men (Aisenbrey and Fasang, 2017; Millett and Kevelson, 2018; Quintini and Manfredi, 2009).

Stronger *educational* backgrounds are among the most consistently reported correlates of positive career outcomes. Young adults with better educated parents, better grades, and higher cognitive skills are more likely than other youth to follow career sequences involving post-secondary attainment leading to higher prestige employment (Aisenbrey and Fasang, 2017; Anyadike-Danes and Mc Vicar, 2005, 2010; Dorsett and Lucchino, 2014; Klug et al., 2019; Quintini and Manfredi, 2009; Ross et al., 2018; Deming, 2021; Millett and Kevelson, 2018; Sirnio et al., 2017). Conversely, individuals with weak academic skills face a higher likelihood of lengthy periods of part-time activity and disconnection from the labor market. Growing evidence also shows a variety of psycho-social skills (e.g., pro-social attitudes and behaviors, social skills, and positive self-evaluation) to be related positively with post-secondary attainment and labor-market success (Deming, 2017; Ross et al., 2018; Millett and Kevelson, 2018; Tayfur et al., 2021).

Career orientation—that is, knowledge and commitment to pursuing education and work in a particular occupation—also has been identified as having a strong influence on the school-work sequence youth follow, although the ability of such measures to predict sequence types has not yet been examined. Training commitment has emerged as a strong predictor of college retention, net of other factors, in a number of studies (e.g., Colquitt et al., 2000; Robbins et al. 2006, 2009).

Most studies have found that access to *financial resources* at the start of young adulthood has a strong positive relationship with careers choices. Higher income and socioeconomic status in families of origin increase, while financial hardship decreases, the odds for school-work sequences involving higher education and decrease the likelihood of disconnection (Anyadike-Danes and McVIcar, 2005, 2010; Karagiannaki, 2017; Millett and Kevelson, 2018; Sirnio et al., 2017). The persistence of effects after controlling for parents' education and other background variables suggests that family resources provide critical support for education-focused career pathways.

Lastly, measures of a variety of other *personal challenges and vulnerabilities* in adolescence/early adulthood are predictive of career sequences. Poorer physical and mental health (Klug et al., 2019; Clayborne et al., 2019; Cornaglia et al., 2015; Hale et al., 2015, 2018); early childbearing (Klug et al., 2019; Lorentzen et al., 2019; Quintini and Manfredi, 2009) and delinquency and criminal justice system involvement (Kang, 2019; Ross et al., 2018) are associated with higher disconnection and less stable employment trajectories.

As well as helping to understand the influences on career formation, school-work sequences also appear to have a strong influence on *subsequent life outcomes*. Analysis of German data show that sequences marked by earlier periods of intermittent employment as compared with more stable employment are associated with a substantial long-term cumulative wage disadvantage and less home ownership (Fauser, 2020, 2022). Multiple studies have established strong positive relationships between the stability of school-work trajectories in young adulthood and long-term mental and physical health (Fan et al., 2018; Giudici and Morselli, 2019; Klug et al., 2019).

2.2. The gap in workforce intervention research

The increased emphasis on career pathways in workforce policy suggests that impacts on sequences of training and employment activities should be a major focus of program evaluations. Such a focus has been to date lacking. Rather, evaluation outcomes have been mainly limited to point-in-time and period measures of education, employment, and other aspects of well-being.

A major reason for this inattention to pathways is the difficulty of obtaining useful summary measures for entire sequences of training and employment. Focal outcomes for impact evaluations must be measured in a comparable way for treatment and control groups—a challenging proposition when comparing steps on pathways across diverse occupations. Although programs may focus on specific steps on job ladders in particular occupations, some treatment group members and most or all control group members are likely to choose different paths. Great variation in the sizes and positions of steps in diverse occupational fields can make it very difficult to find a common standard for gauging progress on pathways.

The advent of sequence analysis offers a promising response to this problem. The method's key virtues lie in its ability to: 1) translate successive spells of training, employment, and labor market inactivity into representations of career sequences that are compared across a wide spectrum of occupations and 2) usefully group individuals on the basis of the similarity of these sequences.

This paper explores and illustrates the potential for applying sequence analysis to workforce evaluations, using data from a well-conducted RCT of Year Up, a national training program for young adults. Unlike most of the literature discussed in the prior section, our possible school-work statuses differentiate work at varying wage levels in order to identify pathways characterized by more and less career progress. The aim is to support tests of hypothesized effects on career sequences implied by Year Up's logic model.

2.3. Program model and hypothesized impacts on school-work sequences

Year Up targets young adults in low-income communities who are at risk of long-term disconnection from education and work. Specifically, it serves youth who are aged 18 to 24; have a high school diploma/equivalent; are motivated; and who, with assistance, have promise to overcome challenges and successfully enter careers in fast-growing technical occupations. The most effective U.S. workforce training programs serve low-income youth and adults that staff deem can benefit and provide them with a wide range of services and supports (Katz et al., 2022).

This paper analyzes data for Year Up's original model, a free-standing program operating in nine cities around the U.S.[1] In 2013-2014—the period when the study sample enrolled in Year Up—the program served over 3,500 young adults. Prior evaluation reports describe the program and evaluation design in detail (Fein and Hamadyk, 2018; Fein et al., 2021; Fein and Dastrup, 2022).

During the first six months of Year Up—the "Learning and Development Phase"—participants attend courses at Year Up full-time. The focus of technical training varies by local office and study cohort. Fields include information technology (IT, the most common emphasis), business operations, financial operations, software development, and sales and customer support. General skills training emphasizes professional (i.e., "soft") skills and English instruction calibrated to needs in business communication. Year Up sites partner with local colleges to arrange for college credit for Year Up coursework.

Year Up's "high support, high expectations" model provides extensive services and sets high standards for professional behavior. Each incoming cohort of young adults is organized into learning communities of about 40 participants and staff to foster supportive social connections. All participants are advised by Year Up staff members, and all staff members serve as a student advisor/coach in addition to other duties. Participants also receive mentoring from outside professionals working in related occupations. Each local office maintains a team of social workers who provide direct services and referrals to help participants address varied life challenges.

[1] The cities include Atlanta, Boston, Chicago, New York, Providence, San Francisco, San Jose, Seattle, and Washington DC. Year Up has developed a variety of newer versions of its basic model, including a college-based version that also operates in multiple locations (Fein et al. 2020).

Participants receive weekly stipends to help cover transportation and other program-related expenses. During the study period, stipends were $150 in the first phase of the program, and $220 in the second. Participants sign a formal contract specifying standards for professional behavior. Infractions trigger stipend reductions and can lead to dismissal from the program.

In the second half of the year—the “Internship Phase”—participants intern at local firms, often Fortune 500 companies. They work at their internship sites full-time for four-and-a-half days a week. Participants return to Year Up each week for a half-day skills workshop during which they share their internship experiences and plan for education and careers after graduation from the program. Towards the end of internships, the emphasis on job search and placement intensifies. Active efforts to support job search and placement continue for up to four months after graduation.

Prior evaluation reports show large increases in average annual earnings of about $8,000 emerging in the second follow-up year (after the program year) and persisting undiminished for at least seven years. Although large for nearly all subgroups and locations examined, the size of earnings impacts varied considerably across subgroups of participants. Effects were larger for participants identifying as White/another race, having stronger educational backgrounds, or reporting low/moderate levels of depressive symptoms than for those identifying as Black or Hispanic, having weaker educational backgrounds, or reporting the most depressive symptoms.

Participating in Year Up increased college enrollment during the first (program) year—when the program co-enrolled many participants at local college partners—but not subsequently. Enrollment rates in the treatment group dropped below rates in the control group in the second year as many of the former moved into full-time jobs. Thereafter, rates for the two groups were similar.

Year Up’s theory of change posits positive long-term benefits from moving young adults into full-time, career-track jobs after they finish the program. The model’s intensity and comprehensiveness reflect recognition of the need to anticipate and address a wide variety of influences on career trajectories discussed in the previous section. In addition to helping secure initial job placements, the model seeks to generate momentum leading to longer-term career progress. Most directly, it fosters skills needed to thrive at work and progress to jobs with higher pay and greater responsibility over time. Once financial situations are secure, Year Up expects that some young adults will return to school and earn further skills and credentials, either at a college (building on credits earned at local colleges during the program) or at other training and certification providers.

This theory yields the following hypotheses about Year Up’s impacts on school-work sequences:

1. Treatment group members will be more likely than their control group counterparts to transition from full-time training to full-time, well-paying jobs and subsequently advance to higher wages.
2. Treatment group members also will be more likely to re-enroll in education and training following initial career-track employment.
3. Treatment group members will be less likely than control group members to experience sustained spells of low-wage work, part-time school or work, or disconnection (i.e., periods with no school or work).

To test these hypotheses, we created a parsimonious set of mutually exclusive school-work statuses and identified every sample member's status in each of the first 36 months after random assignment. The goal was to identify the most parsimonious set of statuses pertinent to the program's logic model.

The resulting set of possible school-work statuses includes attending school (or training) full-time; working full-time at each of a series of hourly wage levels (<$15, $15-19, 20-24, and $25+); attending school or working part-time; and having no school or work activity.

For the sake of parsimony, these categories do not distinguish spells of part-time school – as a sole activity or in combination with part- or full-time work. To assess impacts on returning to school after transitions to well-paying jobs, we compare (in Table 1) the frequency of such transitions for treatment and control group members.[2]

3. Methods

3.1. Experimental design

Recruitment for the experiment ran from January 2013 to August 2014 and enrolled 2,544 program-eligible applicants in the study. Accessing online software, Year Up staff in eight cities randomly assigned program applicants to either a treatment group that was encouraged to enroll in Year Up or a control group that was not allowed to enroll. Randomization generated highly similar groups: of 28 baseline characteristics, only one showed a statistically significant (p<.10) treatment-control difference (Fein and Dastrup, 2022).

[2] We also ran OM analyses for an alternative set of school-work statuses devised to discern the role of part-time school. This set distinguished periods with only part-time school and those with part-time school combined with full-time and part-time work. For the sake of parsimony, this set of statuses collapsed wages from four to two tiers (below $15/hour and $15/hour or above). Echoing the transition counts in Table 1, one of the resulting clusters included a group of treatment group members transitioning to part-time school (mostly combined with full-time low-wage employment) following spells of full-time employment. This cluster included only four percent of the overall sample.

The research team collected outcomes data for both groups at successive follow-up intervals and estimated impacts by calculating the difference between groups in the average values of the outcomes of interest. The experimental design ensures that estimated impacts can be attributed to access to the program and not to unmeasured differences in characteristics or external circumstances of the treatment and control groups (Orr, 1999).

Baseline data for the study sample also show that Year Up succeeded in reaching its target population of disadvantaged young adults. A majority of sample members identified as non-Hispanic Black (54 percent) or Hispanic of any race (31 percent). Many had struggled in high school: 40 percent reported usual grades of C or below, and only 10 percent reported usually receiving A's. About half had attended some college. Nearly two thirds (63 percent) were in families with annual incomes below $30,000. The remaining indicators show varying levels of disadvantage on other fronts. Men (59 percent) outnumbered women (41 percent), though women account for a higher share of participants in Year Up's heavily IT-focused training program than in IT training generally.[3] Most sample members (68 percent) were living with their parents, and few (9 percent) had children.

3.2. Data sources and measures

The principal data on monthly school-work statuses are from a survey conducted three years after random assignment. Seventy-one (71) percent of the original study sample (1,815 individuals) responded to this survey.

Interviewers collected information on all spells of education and work since random assignment. In addition to beginning and ending dates, survey questions ascertained whether each school enrollment spell was full-time, part-time, or a mix of the two (classified as part-time in the analysis). For employment spells, questions ascertained weekly hours and typical hourly wages at the beginning and end of the spell.[4]

These spell data were the basis for constructing indicators of sample members' primary school-work status in each of the first 36 follow-up months. As discussed in Section 2.3, the analysis builds sequences

[3] Women accounted for only 20 percent of recipients of associate degrees in computer science nationally in 2014. See https://www.nsf.gov/statistics/2017/nsf17310/static/data/tab4-1.pdf.

[4] When hours or wages differed at the beginning and end of a spell, we assigned the starting value to months in the first half of the spell and ending values to months in the second half. When such values were missing at either, but not both, ends we assigned the non-missing value to all months. For employment spells with missing hours or wages at both ends, we assigned a school-work status of "missing" in months affected. Judkins et al. (2020) describe additional imputations for missing job spell information at earlier stages of data processing. In the resulting dataset on monthly school-work statuses, status was missing in only 2-3 percent of months. "Missing" was treated as an allowable (eighth) status in sequence analysis.

across the following seven statuses: full-time school; employed full-time at four possible hourly wage levels (<$15, $15-19, $20-24, $25+); part-time school and/or work; and not in school or working. We defined individuals as enrolled in school full-time or working full-time regardless of whether they also reported part-time work or school part-time.[5] We applied Optimum Matching (OM) and cluster analysis methods to these individual sequences of monthly school-work statuses to identify salient underlying patterns, as explained in Section 3.3.

Baseline surveys and a six-year follow-up survey provided additional data for the analysis—supporting measures of hypothesized antecedents and consequences of three-year school-work sequences, respectively.[6] We selected baseline measures to represent influences in each of the five categories discussed in Section 2.1: demographic characteristics (age, gender, race-ethnicity); educational background (usual high school grades, years of college enrollment, parents' college attendance); career orientation (indices of career knowledge and commitment to post-secondary training); financial resources (family income, living with parents); and personal challenges and related life stressors (depressive symptoms index, whether ever arrested, and indices for life challenges and stress).[7]

The six-year survey successfully re-interviewed 1,610 young adults (78 percent) from the three-year survey respondents. This survey was limited to traditional point in time and period measures and did not collect additional information on education and employment spells. As described in the next section, this paper analyzes the degree to which career sequences over the initial 36-months predict three six-year survey outcomes—personal income (annualized from reported income in the month prior to the survey), ability to handle a $400 emergency, and self-reported health—as well as credential receipt based on college records.[8]

Analyses of three- and six-year survey data adjusted for non-response using separate weights created to make each sample as representative as possible of the full research sample on a series of baseline characteristics.[9]

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[5] In rare instances of months with both full-time school and full-time work, we designated full-time school as the primary status.

[6] The six-year survey did not include questions on school and work history due to concerns about interview length.

[7] Judkins et al. (2022, Exhibit A-1) provide operational definitions of these measures.

[8] See Judkins et al. (2022) Appendix C (Exhibits B-3, B-5) for definitions of survey-based measures and Appendix C for the college records-based measure.

[9] Judkins et al. (2021) and (2022) summarize how weights were constructed for the three- and six-year surveys, respectively.

3.3. Analysis methods

3.1.1. Identifying sequence patterns

Optimum Matching (OM) creates a measure of similarity for every possible pair of sequences in the sample by calculating the number of operations needed to change one sequence into the other. Potential operations include insertions and deletions ("indels") and substitutions at one or more positions in the sequence to be transformed. Based on weights, or "costs," assigned to each possible operation (e.g., the costs of indels and substitutions), an algorithm is used to find the combination of alignment operations that minimizes the cost of transforming one sequence to the other in every pair. The analyst then uses cluster analysis to identify groups of individuals with similar sequences, by minimizing average "costs" within groups and maximizing average distances across groups.

There are many ways to assign costs to each indel and substitution, varying in the dimensions of sequences on which similarity is based. Costs can be set to highlight dissimilarities in position or timing (i.e., the time period in which each status occurs), in spell duration (the number of periods spent in a particular status), and in order of spells (the sequence in which different statuses occur). In principle, decisions should emphasize the features of sequences most pertinent to one's research questions and theory. In practice, studies of sequences of school and work activity often have found clustering to be fairly insensitive to alternative cost schemes.[10]

Lacking a concise theoretical rationale for assigning costs, we followed the common practice of applying a constant cost to substitutions, setting indels to half that amount, and testing the sensitivity of cluster solutions to alternative cost schemes.[11, 12] We tested our cluster solution's sensitivity to several measures of sequence distance (i.e., cost), establishing as more similar: 1) substitutions between school-

[10] This regularity implies that the types of career sequences typically studied in general population samples tend to involve relatively few long spells, statuses that change at roughly similar points in time, and spells in these statuses that tend to occur in the same order.

[11] Technically, this approach amounts to equalizing the costs of substitutions and indels, since in a given period a substitution is equivalent to one deletion followed by one insertion.

[12] Sequence analyses in this paper used the R software packages TraMineR and WeightedCluster. See http://traminer.unige.ch/ and https://cran.r-project.org/web/packages/WeightedCluster/vignettes/WeightedCluster.pdf.

work statuses with higher observed transition rates in the overall sample (testing this approach with lower and higher indel costs) and 2) sequences with generally similar longer spells.[13, 14]

The analysis used Partitioning Around the Medoid (PAM) to identify an optimal set of school-work sequence clusters. This method starts by randomly dividing the sample into a specified number of groups and identifies an initial medoid observation for each group. The medoid is the observation with the smallest average sum of distances (costs) from other sequences in the group. Each observation then is assigned to the cluster containing the medoid to which it is closest, and medoids are recalculated. The process repeats until there are no further changes in cluster assignments.

Fit statistics and graphic results for 2, 4, 6, 8, and 10 clusters suggested that an 8-cluster solution provided an optimal representation of patterns for the pooled sample. At .34, the Average Silhouette Width (ASW) for the 8-cluster solution was high compared to other solutions, if lower than the .50 level sometimes suggested as a rule of thumb for acceptable cluster fit (Cornwall, 2015). Methodologists caution against putting too much weight on fit statistics, given that the level and implications of real structure underlying observed sequences cannot be directly ascertained.[15] Rather, they advise: 1) assessing graphical summaries to see if the sequences in each cluster share salient and meaningful attributes and 2) assessing predictive validity through analyses of correlations of cluster membership with hypothesized antecedents and consequents.

We also estimated 8-cluster solutions using the three alternative cost measures. Results were highly similar across the four approaches and slightly favored the constant rate method.[16]

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[13] For some time, analysts favored transition rate (TR) methods because they seemed to “let the data speak” in determining similarity between statuses. The underlying reasoning was that two statuses must be relatively similar if people tend to transition between them often. More recently, TR measures of distance have been criticized for ignoring the direction of transitions between statuses and for potentially violating the “triangle rule,” which requires that the distance between two sequences not depend on other sequences in the sample. In practice, because TRs between particular states in a given period tend to be close to zero, substitution rates tend to be approximately constant and yield cluster solutions nearly identical to constant cost methods (Studer and Ritschard 2016).

[14] The OM spell method, as proposed in Studer and Ritschard (2016), allows the analyst to reduce the cost of indels needed to transform the longer spells in one sequence to the length of similar spells in the reference sequence. The lower the expansion cost, the more weight is assigned to common spells—and sequencing—while higher expansion costs are more sensitive to differences in timing.

[15] Modest fit could have a number of sources: some sequences may be inherently less organized than others; measures of inter-sequence distance may miss important similarities; and random measurement error may add noise to otherwise serviceable solutions.

[16] The ASW for the constant rate solution (.34) was 1) identical to ASW for the transition rates with lower indel costs (i.e., indels set to the maximum observed substitution cost) and 2) slightly larger (better) than that for transition rates with high indel costs (.29) and OM spells with low indel (.28). There was a high degree of agreement in cluster assignments across methods. Cluster assignments using constant costs aligned with

3.3.2. Analysis of sequence antecedents and consequences

To further validate and explore the substantive significance of the resulting clusters, we assessed the degree to which: 1) antecedent (baseline) measures predicted 3-year sequence cluster membership and 2) 3-year sequences predicted outcomes at the six-year follow-up mark.

Like most of the predictive studies reviewed in Section 2, antecedent analyses for this paper involved multinomial logit regression of sequence type on a set of baseline covariates and treatment-control status. The results (in Section 4.2) represent each covariate's effects on the odds of experiencing a particular sequence type relative to the odds for sustained disconnection (the omitted, or reference, sequence type). To increase statistical power and simplify interpretation, we collapsed the eight sequence clusters to six—combining two clusters defined by movement to higher wages (full-time work at $20-24/hour and $25/hour or more) and two clusters involving part-time school or work. We also transformed the five metric indices into standard deviation units with zero means, which improved comparability of their effects.

Analyses of hypothesized consequences (Section 4.3) involved regressing four 6-year outcomes (see Section 2.3) on the 3-year sequence types, controlling for the same baseline covariates used in the antecedent analysis. We used ordinary least squares regression to estimate models for personal income at six years and logistic regression for the three binary outcomes. In addition to assessing the degree to which school-work sequence types predict later outcomes, we analyzed their role as potential mediators of Year Up's impacts on these outcomes.

4. Findings

Our presentation of findings begins with visual assessment of graphs summarizing sequence clusters identified for the pooled sample. Next, we compare distributions across these clusters for treatment and control group members (Section 4.1). Section 4.2 summarizes results from multinomial logit regressions of sequence type on baseline characteristics, and Section 4.3 analyzes how well three-year sequences

assignments using TR costs 99 percent of the time, with assignments using high indel TR costs 84 percent of the time, and with assignments based on Studer and Ritschard's (2016) OM spells method (with indel costs set low to emphasize common longer spells) 81 percent of the time. Visual inspection showed a high degree of similarity in clusters' status distributions across cost methods. In a few clusters, changing indel costs affected the degree to which the similarity of treatment and control group members' spells was driven by similarity in spells during or after the first of the three follow-up years—a period in which the vast majority of treatment group members were in education (i.e., Year Up training). For example, the OM spell solution combined treatment and control group sequences with relatively long spells of part-time school or work after the first year, notwithstanding the treatment (but not control) group's long full-time education spells in the first year.

predict six-year outcomes. Finally, Section 4.4 examines results from separate cluster analyses run for treatment and control group members.

4.1. Primary school-work sequence patterns in the pooled sample

Two graphs commonly used to summarize sequences are the *all-sequence plots* and the *status distribution graphs*. Figures 1 and 2 show the all-sequence plots and status distributions for each of the eight sequence clusters, respectively. The all-sequence plots include a thin bar for each sequence in the cluster, sorting bars by first and subsequent statuses in each month. The status distribution graphs – stacked line graphs summing to 100 percent in each month – plot the percent of cluster members in each status in successive months.

The all-sequence plots preserve the actual individual sequences in each cluster and help to reinforce the connection between cluster and sequence—the unit of analysis. Status distributions (Figure 2) provide a crisp visual summary of shifts in the proportion of cluster members in each school and work status over time. Clusters are ordered on the page according to their consistency with Year Up's logic model, with the most and least favorable sequences appearing in the figure's upper left and lower right panels, respectively.

The two sets of graphs convey a similar message. The vast majority of sequences in Cluster 1 start with about 12 months of full-time school (brown) and transition directly to well-paying full-time jobs (dark green), while small fractions step to well-paying jobs after spending some time in lower-paying jobs (lighter green) or spells with neither work or school (red). The all-sequence plots (Figure 1) show these transitions directly, whereas the status distribution graphs (Figure 2) make prominence of various statuses at successive follow-up intervals somewhat easier to grasp.

Three of the eight patterns reflect sequences Year Up sought to promote, and five do not. Clusters 1-3 show a sharp transition from full-time training (brown) to full-time work at career-track hourly wage levels after the 12th follow-up month ($25+ for Cluster 1, $20-24 for Cluster 2, and $15-19 for Cluster 3). In each of these clusters, increasing percentages of the sample with darker shades of green in later months hint at modest movement to higher wage tiers during the follow-up period. Clusters 4-8 reflect types of school-work trajectories that Year Up did *not* seek to foster. These patterns include relatively long spells of full-time school not yet leading to full-time work in the three-year follow-up period (brown in Cluster 4); full-time, low-wage employment (yellow in Cluster 5); part-time school and/or part-time work (blue in Clusters 6 and 7); and disconnection (red in Cluster 8).

Two in five treatment group members (40 percent), but fewer than one in ten control group members (9 percent), fell into Clusters 1-3 (Table 1)—clusters involving transitions to full-time jobs at $15 an hour or above. Control group members were more likely than treatment group members to experience long spells of full-time low-wage employment (Cluster 5) and part-time work or school (Clusters 6 and 7). Treatment-control differences in these clusters are statistically significant. In contrast, differences in the fractions of the two groups sustained long spells of full-time school (Cluster 4) or disconnection (Cluster 8) are small and not statistically different. The bottom panel of Table 1 summarizes transitions from initial full-time jobs to higher wage tiers and to additional spells of training. Fourteen percent of treatment group members left full-time school for an initial full-time job paying at least $15/hour (i.e., career track) and then progressed to a higher wage level. Only one percent of control group members followed this pattern. Counting transitions to higher wages following initial transitions from training to any job (i.e., including low-wage positions at <$15/hour), 22 percent of treatment and 4 percent of control group members experienced such transitions.

The next two rows show the fractions progressing to a higher wage tier for all sample members who held a full-time job, regardless of whether they had prior training. Considering young adults who ever held a career-track job (i.e., $15+/hour) and then advanced to a higher wage tier, significantly more treatment than control group members (14 compared to 5 percent) experienced such advancement. Considering wage increases to those who held any full-time job – including those paying under $15/hour – similar percentages of treatment and control group members (23, compared to 20, percent) experienced advancement.[17] Similar wage progression rates help to explain why, after the initial program year, impacts on average annual earnings increased by very similar dollar amounts through the end of a seven-year follow-up period (Fein and Dastrup, 2022).

Another indicator of career progress is pursuit of further training after taking an initial career-track job. As discussed in this paper's introduction, career pathways proponents believe that low-income youth and adults will be better able to progress in careers if training is formulated as a series of manageable steps.

To encourage returns to college, Year Up arranged with college partners to provide a base of credits for completing Year Up courses. The logic model posits that young adults will be in an improved position to continue their studies after they secure good-paying jobs. Statistics suggest some transitions of this kind, if not a large number. Thirteen (13) percent of treatment group members returned to school (full- or part-time) after a period of work in a full-time, career-track ($15+/hour) job that had followed an initial training spell.[18] The corresponding figure for control group members was only 5 percent.[19]

[17] The former, but not the latter, impact is statistically significant.

[18] This statistic includes returns to training that were concurrent with full-time jobs at $15+/hour.

[19] The treatment-control difference (eight percentage points) is statistically significant at p<.01.

4.2. Baseline characteristics predicting 3-year school-work sequences

In these analyses, we treat school-work cluster membership as a categorical outcome and examine the baseline characteristics predicting sequence type. Estimates in Table 2 represent each characteristic's influence on the odds of experiencing each sequence type compared to the odds for sustained disconnection (the reference type), net of other covariates.[20]

Statistics in the first row summarize Year Up's impacts on school-work sequences. Recalling from Table 1 that Year Up had no effect on sustained disconnection, effects in Table 2 greater than one imply positive impacts while effects less than one imply negative impacts. The estimates show that Year Up substantially increased the odds for higher earning trajectories, reduced the odds for part-time sequences, and reduced somewhat the odds of sustained full-time school enrollment.

Most, though not all, of the remaining characteristics had statistically significant associations with sequence type. Young adults who were older at random assignment were slightly more likely than those who were younger to move into the highest wage jobs and substantially less likely to sustain full-time school enrollment. Gender and race-ethnicity had mostly little effect, although the odds of entering the highest wage pathway were slightly lower for blacks than for the Hispanic and white/another race-ethnicity groups. Stronger educational backgrounds (e.g., better high school grades, prior college experience) predicted higher wage and sustained school trajectories in particular and generally reduced the odds for disconnection.[21] Parents' college attendance had comparatively little effect—again, perhaps because young adults' educational outcomes already reflected parental influences.

Low family incomes in the year prior to study intake reduce the odds for pathways leading to sustained full-time work – especially among those in the highest wage tier – or full-time school. Living with parents increased the odds for the sustained full-time school and part-time school-work pathways, signaling the role such arrangements can play in helping with living expenses while attending school.

Career knowledge – an index of self-efficacy in career planning – was not significantly related to career sequences. Commitment to training increased the odds for sustained full-time school but had no effect on other pathways.

Indicators for several personal vulnerabilities and challenges were associated negatively with pathways from training to full-time work in the $15-19 and $20+ wage tiers. Depressive symptoms and prior

[20] Sustained disconnection provides a useful standard for assessing the effects of Year Up and other personal characteristics given that the program targets young adults at risk of disconnection.

[21] Young adults with a year or more of prior college experience were more likely to follow any of the five alternative paths than to experience sustained disconnection.

arrests effects reduced the likelihood of full-time work at $15-19 wage tier, while an index of life challenges reduced the odds of following both upper wage pathways. In contrast, stress at baseline was positively associated with favorable sequences (e.g., increased odds for higher wage pathways). Stress is understood to have positive, as well as negative, manifestations: perhaps the residual variance in our measure is positive after controlling for depression and life challenges.

Last, youth in the most tech-focused Year Up location had substantially higher odds of moving into the highest wage tier, attesting to the role that local labor markets can play in determining outcomes.

Estimates in Table 2 represent the weighted average of each predictors' effects on outcomes for youth in the treatment and control groups.[22] Covariates could have different effects in the two groups due to differential responses to Year Up. In general, correlations with sequence type might be stronger or weaker for treatment, compared with control, group members depending on the nature of each factor's moderating influence.

To explore potential moderating influences, we added interactions between treatment-control status and four characteristics to the model in Table 2, selecting characteristics with relatively strong main effects, namely: educational attainment, family income, life challenges, and stress. Table 3 summarizes the resulting coefficients, expressed as effects on the log odds for different sequence types to facilitate interpretation.[23]

As a set, the interactions significantly improved model fit ($p<.01$). Treatment-control differences in the effects of family income are evident for multiple sequence types, more type-specific for challenges and stress, and largely absent for educational attainment. For control group members, lower-income backgrounds increase the likelihood of sequences characterized by low-wage work and part-time activity and (in the lowest income group) decrease the likelihood of a high-wage ($20+ per hour) sequence. In the treatment group, such effects are largely attenuated: the effect on alternatives to disconnection (the reference group) is relatively similar across income categories. Those with greater life challenges in the control group, but not those in the treatment group, have lower chances of following a higher-wage sequences. In contrast, stress is mostly unrelated to sequence type among control group members,

[22] The main effects in Table 2 weight influences in the treatment group more heavily than influences in the control group, owing to the study's 2:1 random assignment ratio (producing a sample comprised of 2/3 treatment and 1/3 control group members).

[23] Because covariate effects are multiplicative in an odds specification, the effects of one covariate conditioned on the level of another (and the associated standard errors) will depend on average levels of the remaining covariates in the model.

while higher levels of stress for those in the treatment group increase the likelihood of following a relatively high-wage sequence.

4.3. Three-year school-work sequences as predictors of 6-year outcomes

Given the scope of developmental challenges during young adulthood, it is reasonable to expect that transitions observed during a three-year window will exert a strong influence on longer-term school-work trajectories. To assess this proposition, we analyzed the relationship between 3-year school-work sequence type and a set of outcomes measured six years following enrollment in the study sample. We also tested the degree to which three-year sequences account for (i.e., mediate) Year Up's impacts on 6-year outcomes.

Table 4 summarizes the estimated effects of adding sequence type and treatment-control status variables to the model separately (Models I and II) and together (Model III) in models for 6-year outcomes. All models also control for the entire set of baseline covariates (not shown in Table 4).

Results for Model I show that young adults with higher-wage trajectories in the first three years had more favorable outcomes at six years. Compared to sample members in the sustained disconnection group (the reference, or omitted, pathway), those in higher-wage pathways ($20+/hour) averaged $19,000 more in personal income, were 2.2 times more likely to be able to handle a $400 emergency and were 1.7 times more likely to report being in very good or excellent health. Young adults moving to the second highest wage tier ($15-19/hour) also had higher average incomes and better ability to withstand financial emergencies. Financial outcomes for the remaining trajectories did not differ significantly from those for the sustained disconnection cluster.

As might be expected, education outcomes were much more favorable for young adults in the sustained education pathway: their odds of receiving a 1-year college credential were 7.2 times higher than for the reference group. Following the part time school/work pathway also increased the odds for credential receipt, albeit by a smaller factor (1.5). Young adults in the full-time school pathway also were slightly less likely to report favorable health than those in the omitted pathway, although this finding is barely statistically significant (p=.094 in Model I, p=.099 in Model III).

Assignment to the Year Up treatment group was associated with higher average personal income, better ability to handle a $400 emergency, and better (self-reported) health but not with college credential receipt (Model II). Impacts vanished after adding school-work trajectory indicators to the model (Model III), indicating that three-year school-work trajectories fully mediated Year Up's impacts on financial and health outcomes.

4.4. Results from separate sequence analyses for treatment and control group members

For a closer look at school-work sequences experienced by treatment and control group members, we ran the cluster analysis separately for each group. In this case, six-cluster solutions captured salient patterns in each group.[24] Figures 3 and 4 provide the resulting status distribution graphs for treatment and control group members, respectively. These exhibits use letters rather than numbers to identify clusters to underscore that the clusters are based on somewhat different samples than clusters based on the pooled data.

Salient sequence patterns mostly resemble those in the pooled data. As seen in Figure 3, high proportions of treatment group members in all clusters sustained full-time training for 12 months and then varyingly transitioned to full-time, career-track jobs (Clusters A and B); full-time school (Cluster C); low-wage employment (Cluster D); part-time activity (Cluster E); or persistent disconnection (Cluster F).

In the control group (Figure 4), patterns in four clusters mirror results from the pooled analyses (aside from the initial 12-month training spell). These patterns include sustained spells of full-time school (Cluster H), full-time low-wage work (Cluster I), part-time school or work (Cluster K), and disconnection (Cluster L).

The analysis also identifies two clusters whose patterns were not salient in the pooled data. Cluster G identifies a relatively small subgroup that started the follow-up period in diverse school-work statuses and transitioned to full-time jobs at $15-19/hour. Cluster J is dominated by sequences involving transitions from no school/work to part-time activity, and from part-time activity to full-time low-wage employment. The latter two patterns appear to capture most of the upward wage mobility responsible for increases in average earnings in the control group overall.

5. Discussion

The growing focus on career pathways in U.S. workforce policy has increased interest in measuring impacts on career trajectories in training program evaluations. This paper has shown that sequence analysis with Optimal Matching can be useful in analyzing impacts on sequences of school and work activities in randomized controlled trials. Our analyses illuminate the shifts in career trajectories underlying one leading training program's especially large impacts on average earnings.

[24] Average Silhouette Width (ASW) for the six-cluster solution was .375 for the treatment group and .340 for the control group.

Cluster analysis for the pooled Year Up sample revealed eight salient school-to-work sequence patterns. Distinctions between the eight patterns were visually sharp, largely insensitive to alternative measures of sequence distance, and associated with baseline factors and six-year outcomes in reasonable ways.

Treatment-control comparisons of sequence types supported some, if not all, of our hypotheses for Year Up's effects on sequences. Bolstering Hypothesis 1, transitions from full-time training to full-time work at $15+/hour or above and progression to higher wages from jobs starting at $15/above were substantially more prevalent for treatment than control group members. Support for Hypothesis 2 – of increased enrollment in education (part or full-time) after an initial career-track job – is weak. That treatment group members were somewhat more likely than control group members to follow such sequences reflects mainly the much larger share of treatment than control group youth having moved to full-time jobs at $15+/hour after Year Up. The fraction of treatment group members sustaining full-time school with little/no interval of work following Year Up, 11 percent, is slightly smaller than the fraction of control group members sustaining full-time school over the three-year period (14 percent).[25] Support for Hypothesis 3 is mixed. Sequences involving sustained spells of low-wage work or part-time school/work were substantially less likely for treatment than control group members, as expected. Year Up had little effect on chronic disconnection: nearly identical fractions of treatment (21 percent) and control (18 percent) group members followed this path.

Predictive analyses helped to validate and understand the patterns distinguished across sequence clusters. As in prior studies, educational backgrounds, financial resources, and personal challenges at the outset of young adulthood strongly predicted sequence type. Analysis of interactions with treatment status indicate that exposure to Year Up attenuated the negative effects of some factors (e.g., low family income) on career outcomes and ameliorated the effects of others (e.g., stress and life challenges).

Prior analyses have found that, regardless of socioeconomic backgrounds, young women tend to be more likely than young men to experience disconnection and reduced earnings (Millett & Kevelson, 2018; Ross et al., 2018). These studies have identified labor force inactivity associated with childbearing as one likely contributing factor. Although gender was not associated with sustained disconnection in our full sample (a finding that did not vary by race-ethnicity or family income), additional tabulations of three-year survey do hint at a fertility connection. Whereas 31 percent of women in the sustained disconnection cluster reported having had a birth since study intake, only 7 to 15 percent of those in the

[25] Although the difference (three percentage points) is not statistically significant in the simple comparison (Exhibit 3), the multinomial logit results (Exhibit 4) indicate a statistically significant treatment effect on the odds for sustained full-time school (p<.01). Period measures showing negative impacts on college enrollment in the second follow-up year are consistent with the latter finding (Fein et al., 2021).

higher wage and sustained full-time school pathways did so. The lack of an overall gender difference may imply that men experienced counterbalancing challenges leading to disconnection.

The absence of gender differences in the odds for higher wage trajectories also is notable given Year Up's focus on IT careers, a sector traditionally dominated by men (Joseph et al., 2012). The findings show that well-designed workforce training can create viable pathways to tech careers for women as well as men.

Strong associations between three-year school-work sequences and six-year outcomes add to substantive evidence on the importance of the earliest young adult years (Arnett, 2004). After conditioning on a wide set of background factors, three-year sequences predicted not only conceptually proximal economic and educational outcomes but also the more distal outcome self-reported health. Furthermore, the three-year sequences fully mediated the impacts Year Up had on three of the four outcomes (personal income, ability to handle $400 emergency, and self-reported health).

The findings have a number of important practical implications. Most generally, favorable impacts on career pathways bolster the case for scaling programs like Year Up. At the same time, modest rates of advancement to higher wage tiers seen for sequences in favorable clusters suggest that additional training and supports may be needed in the longer term to capitalize on those initial wage gains. And substantial fractions of young adults with less favorable sequences might benefit from strengthened supports during the initial program year. Notably, the program had little effect on the one in five such young adults who experienced sustained disconnection after finishing (or, for some, after dropping out of) the program. These findings reinforce calls for research to support continuous improvements aimed at increasing equity in impacts across subgroups.

Our analysis is subject to several limitations. First, data on school and work histories were collected in PACE three-year survey but not in the six-year survey. Future evaluations should make provisions for longer-term analysis, either by including history data in later survey waves or by obtaining permissions needed to analyze jointly administrative data on school and work activities. Second, although Partitioning around the Medioid is an efficient and widely used cluster analysis algorithm, it does not support testing for improved fit with increasing numbers of cluster solutions. Hierarchical clustering methods should be used when such testing and cluster branching are of interest. Finally, although the school and work activities analyzed here are one useful way to standardize career trajectories, future studies should explore sequences involving other measures of career steps.

This study illustrates some of the ways that sequence analysis can deepen our understanding of intervention effects. Similar analyses could be informative in studies of other workforce and education programs. Analysis of sequences in other outcomes also could be informative in impact studies of a much broader range of interventions—including, for example, developmental milestones for early childhood programs, sex and contraceptive behavior for teen pregnancy prevention interventions, interpersonal interactions for healthy relationship programs, and spending and saving behaviors for financial literacy programs. Possible data sources for such studies include surveys, administrative records, direct observation, biometric measurement, and diary methods.

Future evaluations of programs for young adults should consider extending analysis to family formation—another critical dimension of the transition to adulthood. In addition to separate analysis of sequences in family formation statuses and events (e.g., living with parents, cohabitation, marriage, and childbearing), advances in methods for joint analysis of sequences in multiple domains (e.g., Aisenbrey and Fasang, 2017; Gauthier et al., 2010; and Sirnio et al., 2017) open possibilities for exploring the connections between impacts on sequences in different spheres of emerging adulthood.

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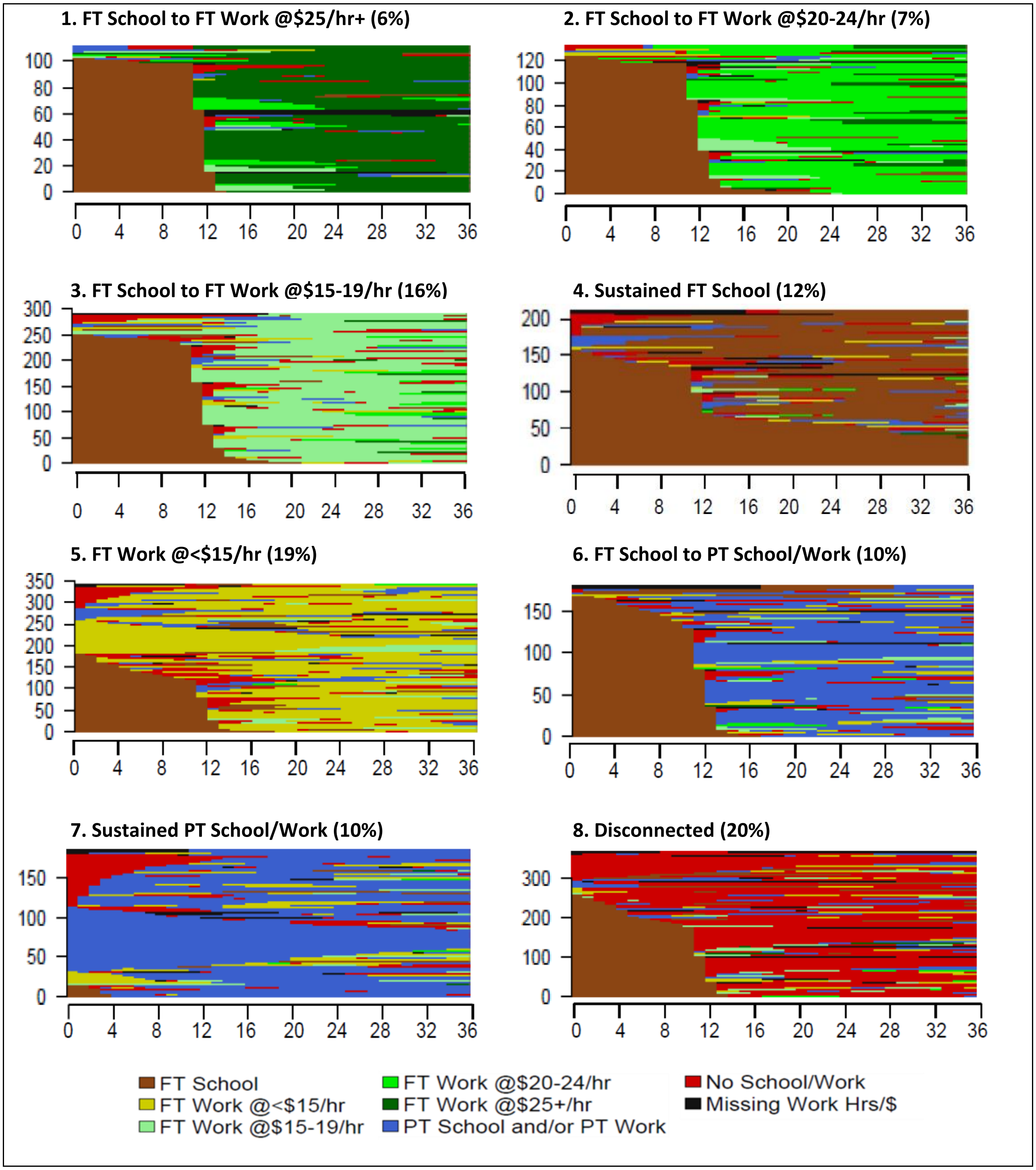
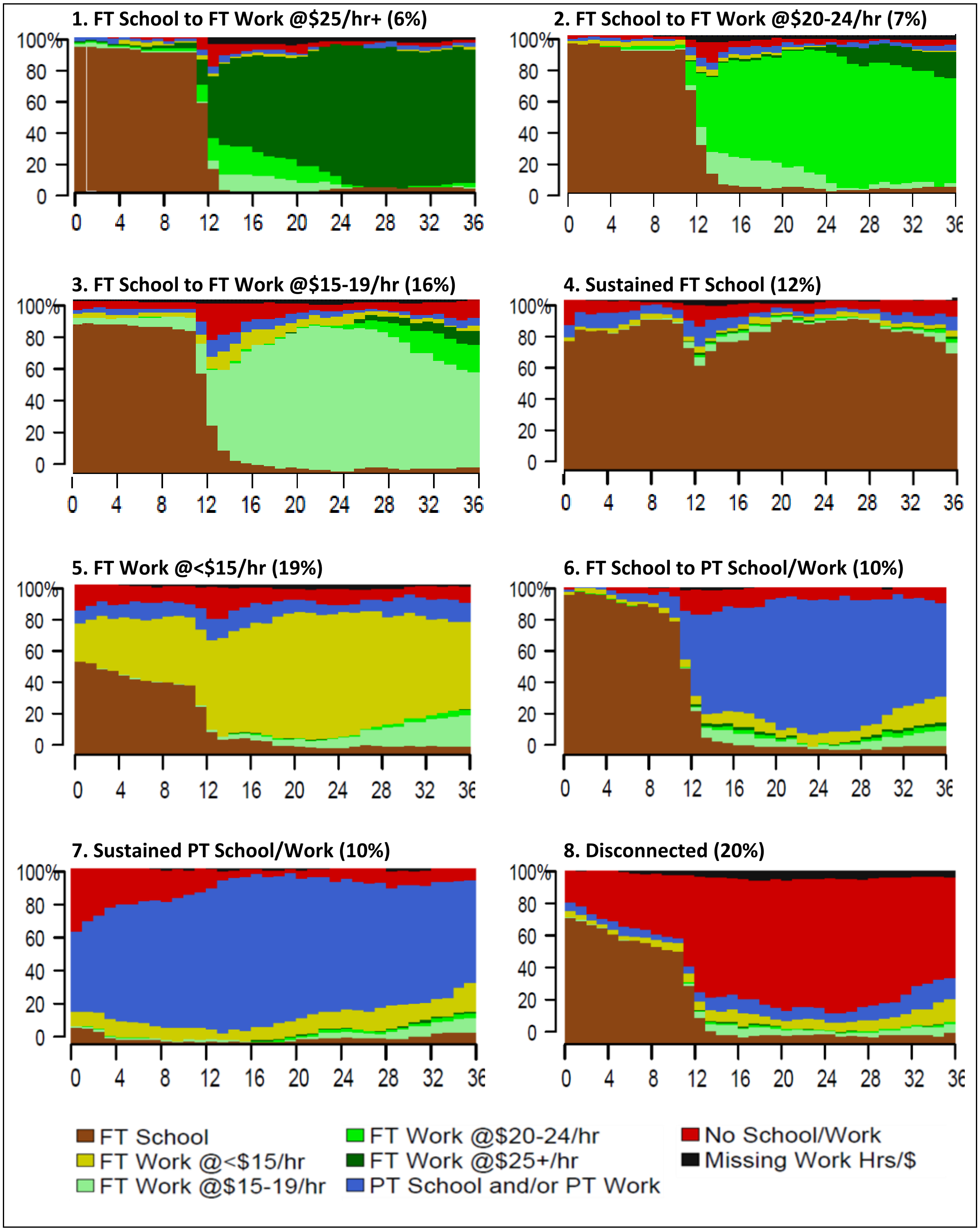
Figure 1: Individual School-Work Sequence Plots for Clusters Identified in the Pooled (Treatment and Control) Sample (Indexing Number of Sequences on Y axis and Percent of Sample in Graph Titles)



Note: Analyses in this figure are based on monthly school-work statuses derived from spell data in the three-year follow-up survey. Rows in each graph represent the individual sequences assigned to each group by cluster analysis. Colored row segments indicate each individual's monthly school-work status over the 36-month follow-up period (X axis). The number of individuals assigned to each cluster is indexed in the Y axis.

Figure 2: Percent in Various School-Work Statuses for Clusters Identified in the Pooled (Treatment and Control) Sample (Showing Percent of Sample in Each Cluster in Graph Titles)



Note: Analyses in this figure are based on monthly school-work statuses derived from spell data in the three-year follow-up survey. Shaded areas in each graph summarize the proportions of individuals in various school-work statuses each month over the 36-month follow-up period.

Table 1

Percent by Type of School-Work Sequence and Percent Experiencing of Selected Transitions, by Treatment–Control Status (%s)

Outcome		Treatment	Control	Impact
Percent of Sample in School-Work Cluster				
1.	FT school to FT work @$25+/hour	8.6	1.3	7.3 ***
2.	FT school to FT work @$20-24/hour	10.5	1.3	9.2 ***
3.	FT school to FT work @$15-19/hour	20.8	6.8	14.0 ***
4.	Sustained FT school	10.5	13.8	-3.3
5.	FT school to FT work @<$15/hour	14.4	27.2	-12.8 ***
6.	FT school to PT school/work	13.4	3.2	10.2 ***
7.	Sustained PT school/work	1.8	26.4	-24.6 ***
8.	Disconnected	20.9	18.4	2.5
	All clusters	100.0	100.0	
Percent of Sample Experiencing Selected Transitions during the First Three Follow-up Years				
FT school →FT work @$15+/hr → Wage increase		13.6	1.3	12.3 ***
FT school →FT work @any wage → Wage increase		22.3	4.0	18.3 ***
FT work @$15+/hr → Wage increase		13.6	4.7	8.9 ***
FT work @any wage → Wage increase		22.7	20.1	2.6
FT/PT school →FT work@$15+ →FT/PT school		13.4	5.1	8.3 ***
Sample Size		1,191	624	

Note: Analyses in this table are based on monthly school-work statuses derived from spell data in the three-year follow-up survey. Percentages differ for treatment and control groups: ***at the 1-percent, **at the 5-percent, *at the 10-percent level. Statistics in the bottom summarize the percent of sample members experiencing each combination of transitions at some point during the follow-up period. For example, the first row identifies young adults who ever moved to a higher wage tier after initially transitioning from full-time school to a spell of full-time work paying at least $15/hour. The last row identifies sample members with a subsequent return to training who initially transitioned from training to full-time work at $15/hour or more.

Table 2

Effects of Treatment-Control Status and Other Baseline Characteristics on the Odds for Specified Sequences Relative to the Reference Sequence Sustained Disconnection (Standard Errors in Parentheses)

	Effect on Odds for Each Sequence Type (Compared to Odds for Omitted Reference Type: Sustained Disconnection)				
Baseline Characteristic	FT School to FT Work @$20+	FT School to FT Work @$15-19	Sustained FT School	FT School to FT Work @<$15	Sustained PT School/ Work
Treatment-control status					
Treatment (ref: control)	8.372 ***	2.858 ***	0.646 ***	0.441 ***	0.412 ***
	(0.254)	(0.175)	(0.159)	(0.135)	(0.133)
Age (ref: 18-20)					
21-24	1.325 *	0.931	0.433 ***	0.813	0.767 *
	(0.169)	(0.148)	(0.164)	(0.140)	(0.137)
Gender (ref: male)					
Female	1.197	1.028	0.778	0.832	1.002
	(0.168)	(0.149)	(0.163)	(0.141)	(0.139)
Race-ethnicity (ref: white/another race)					
Non-Hispanic black	0.636 *	0.902	0.847	1.236	1.367
	(0.233)	(0.226)	(0.236)	(0.220)	(0.214)
Hispanic	1.069	1.346	0.772	1.115	1.328
	(0.237)	(0.234)	(0.252)	(0.234)	(0.225)
Usual high school grades (ref: C or below)					
Mostly Bs	1.137	0.883	1.504 **	0.940	1.044
	(0.168)	(0.149)	(0.173)	(0.141)	(0.138)
Mostly As	1.851 **	1.157	2.193 ***	1.139	0.838
	(0.261)	(0.248)	(0.259)	(0.239)	(0.249)
Educational attainment (ref: high school)					
<1 year of college	1.705 ***	1.476 **	1.426 *	1.087	1.657 ***
	(0.198)	(0.175)	(0.205)	(0.171)	(0.162)
1+ year of college	2.243 ***	1.677 ***	3.411 ***	1.541 **	1.856 ***
	(0.195)	(0.184)	(0.192)	(0.175)	(0.173)
Either parent attended college (ref: no)					
Yes	0.855	0.762 *	0.883	0.843	0.959
	(0.161)	(0.144)	(0.160)	(0.137)	(0.134)
Family income in prior year (ref: $30,000+)					
Under $15,000	0.385 ***	0.704 **	0.691 **	0.681 **	1.194
	(0.194)	(0.165)	(0.186)	(0.161)	(0.159)
$15,000-29,999	0.836	0.710 *	0.955	1.062	1.455 **
	(0.191)	(0.186)	(0.198)	(0.171)	(0.171)
Living with parents (ref: no)					
Yes	1.007	1.082	1.441 **	1.234	1.496 ***
	(0.174)	(0.154)	(0.173)	(0.145)	(0.144)

Baseline Characteristic	FT School to FT Work @$20+	FT School to FT Work @$15-19	Sustained FT School	FT School to FT Work @<$15	Sustained PT School/ Work
	Effect on Odds for Each Sequence Type (Compared to Odds for Omitted Reference Type: Sustained Disconnection)				
Career Knowledge Index	1.107	1.076	1.020	1.064	0.954
	(0.087)	(0.078)	(0.086)	(0.074)	(0.073)
Training Commitment Index	0.882	0.991	1.185 *	1.086	0.995
	(0.084)	(0.079)	(0.092)	(0.075)	(0.070)
Depressive Symptoms Index	0.869	0.762 ***	0.978	0.882	1.041
	(0.099)	(0.091)	(0.096)	(0.084)	(0.080)
Ever arrested (ref: no)					
Yes	0.889	0.573 ***	0.948	1.029	0.803
	(0.202)	(0.196)	(0.210)	(0.169)	(0.172)
Life Challenges Index	0.717 ***	0.778 ***	0.985	0.920	0.974
	(0.095)	(0.083)	(0.085)	(0.074)	(0.071)
Stress Index	1.203 *	1.219 **	1.057	1.138	1.029
	(0.100)	(0.089)	(0.101)	(0.086)	(0.085)
Local economy					
Highest tech site (ref: other sites)	3.186 ***	0.920	0.644	0.250 ***	1.012
	(0.231)	(0.256)	(0.294)	(0.336)	(0.230)
Sample size (Disconnected=364)	244	290	211	341	365

Note: Analyses in this table utilize data from baseline surveys administered at study intake and the three-year follow-up survey. Asterisks flag characteristics for which the relative odds for a particular sequence type differ from the reference type (sustained disconnection): ***at the 1-percent, **at the 5-percent, *at the 10-percent level.

Table 3

Effects of Interactions between Treatment-Control Status and Selected Baseline Characteristics on the Log Odds for Specified Sequences Relative to the Reference Sequence Sustained Disconnection (Standard Errors in Parentheses)

	Effect on Sequence Type Compared to Reference Type (Sustained Disconnection)				
Characteristics at Baseline	FT School to FT Work @$20+	FT School to FT Work @$15-19	Sustained FT School	FT School to FT Work @<$15	Sustained PT School/ Work
Treatment-control status					
Treatment (ref: control)	2.022 ***	1.092 ***	0.447	0.247	0.048
	(0.661)	(0.394)	(0.355)	(0.306)	(0.296)
Educational attainment (ref: high school)					
<1 year of college	0.218 **	0.201 **	0.302 **	-0.013	0.114
	(0.107)	(0.097)	(0.125)	(0.111)	(0.106)
Treatment*<1 year of college	0.399	-0.148	-0.312	0.133	0.302 *
	(0.309)	(0.229)	(0.219)	(0.176)	(0.166)
1+ year of college	0.407 ***	0.285 ***	0.679 ***	0.212 *	0.210 *
	(0.106)	(0.103)	(0.119)	(0.111)	(0.112)
Treatment *1+ year of college	-0.208	-0.174	-0.153	-0.013	0.181
	(0.323)	(0.221)	(0.187)	(0.172)	(0.169)
Family income in prior year (ref: $30,000+)					
Under $15,000	-0.337 ***	-0.077	-0.161	0.020	0.354 ***
	(0.103)	(0.092)	(0.116)	(0.103)	(0.106)
Treatment*Under $15,000	-0.878 **	-0.332	-0.186	-0.593 ***	-0.664 ***
	(0.436)	(0.208)	(0.189)	(0.164)	(0.163)
$15,000-29,000	0.029	-0.099	0.058	0.226 **	0.459 ***
	(0.106)	(0.107)	(0.124)	(0.113)	(0.116)
Treatment*$15,000-29,999	-0.510 *	-0.146	-0.305	-0.549 ***	-0.660 ***
	(0.300)	(0.225)	(0.208)	(0.178)	(0.179)
Life Challenges Index					
Life challenges	-0.360 ***	-0.235 **	-0.043	0.041	-0.073
	(0.102)	(0.091)	(0.104)	(0.089)	(0.089)
Treatment * Life challenges	0.396	-0.166	0.021	-0.359 **	0.061
	(0.281)	(0.233)	(0.174)	(0.156)	(0.147)
Stress Index					
Stress	0.130	0.218 **	0.099	0.051	0.039
	(0.106)	(0.097)	(0.119)	(0.104)	(0.103)
Treatment * Stress	0.739 **	-0.204	-0.097	0.158	-0.040
	(0.289)	(0.202)	(0.175)	(0.151)	(0.146)

Note: Analyses in this table utilize data from baseline surveys administered at study intake and the three-year follow-up survey. Asterisks flag effects for which the log odds for a sequence type differ from the log odds for the reference type (sustained disconnection): ***at the 1-percent, **at the 5-percent, *at the 10-percent level. The first row for each characteristic represents effects for control group members, and effects in rows labeled "Treatment * [Covariate]" represent the difference between effects in the treatment and control groups. Estimates represent effects on the log odds for a sequence type rather than odds as in Exhibit 2 to facilitate interpretation of interaction effects. In addition to characteristics involving interactions (entered simultaneously), the multinomial logit model included all other baseline characteristics shown in Table 2.

Table 4

Effects of Three-Year Sequence Type and Treatment-Control Status on Selected Outcomes Measured after Six Years of Follow-up (Standard Errors in Parentheses)

	Avg Annual Personal Income ($)			Can Handle $400 Emergency (Odds)		
Covariate	I	II	III	I	II	III
Three-year sequence type (ref: Disconnected)						
FT School to FT Work @$20+/hr	18,777 ***		18,822 ***	2.234 ***		2.169 ***
	(2,049)		(2,078)	(0.175)		(0.177)
FT School to FT Work @$15-19/hr	9,835 ***		9,863 ***	2.254 ***		2.213 ***
	(1,872)		(1,886)	(0.158)		(0.159)
Sustained FT School	450		430	1.237		1.255
	(2,100)		(2,106)	(0.172)		(0.172)
FT School to FT Work @<$15/hr	-1,859		-1,891	1.062		1.087
	(1,791)		(1,809)	(0.147)		(0.148)
Sustained PT School/Work	-2,413		-2,447	0.984		1.008
	(1,760)		(1,780)	(0.144)		(0.146)
Treatment-control status						
Treatment (ref: Control)		4,974 ***	-165		1.383 ***	1.118
		(1,232)	(1,264)		(0.097)	(0.104)
Adjusted R^2	0.157	0.073	0.156			
-2 Log Likelihood				2,706	2,750	2,704
Degrees of freedom	24	20	25	24	20	25

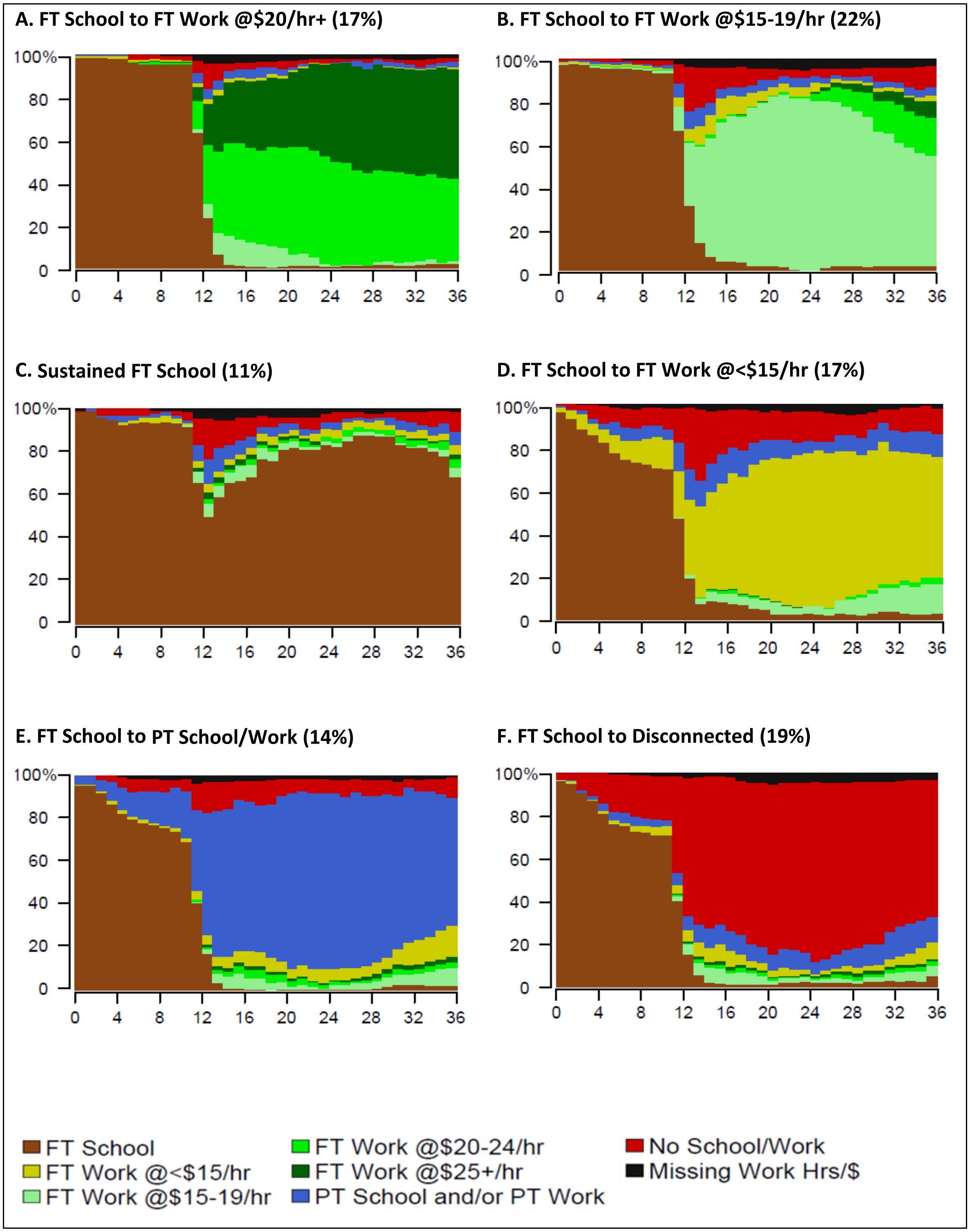
Continued

Table 4 (cont.)

	Received 1-Year Credential (Odds)			Health is Very Good/Excellent (Odds)		
Covariate	I	II	III	I	II	III
Three-year sequence type						
(ref: Disconnected)						
FT School to FT Work						
@$20+/hr	1.223		1.209	1.730 ***		1.707 **
	(0.257)		(0.261)	(0.209)		(0.211)
FT School to FT Work						
@$15-19/hr	1.001		0.994	1.197		1.185
	(0.257)		(0.258)	(0.175)		(0.176)
Sustained FT School	7.224 ***		7.250 ***	0.729 *		0.733 *
	(0.217)		(0.217)	(0.187)		(0.188)
FT School to FT Work						
@<$15/hr	0.962		0.971	0.790		0.798
	(0.249)		(0.251)	(0.161)		(0.162)
Sustained PT School/Work	1.531 *		1.543 *	0.827		0.837
	(0.222)		(0.224)	(0.159)		(0.161)
Treatment-control status						
Treatment (ref: Control)		0.920	1.041		1.244 **	1.054
		(0.131)	(0.147)		(0.107)	(0.114)
Adjusted R^2						
-2 Log Likelihood	1,591	1,736	1,591	2,326	2,346	2,326
Degrees of freedom	24	20	25	24	20	25

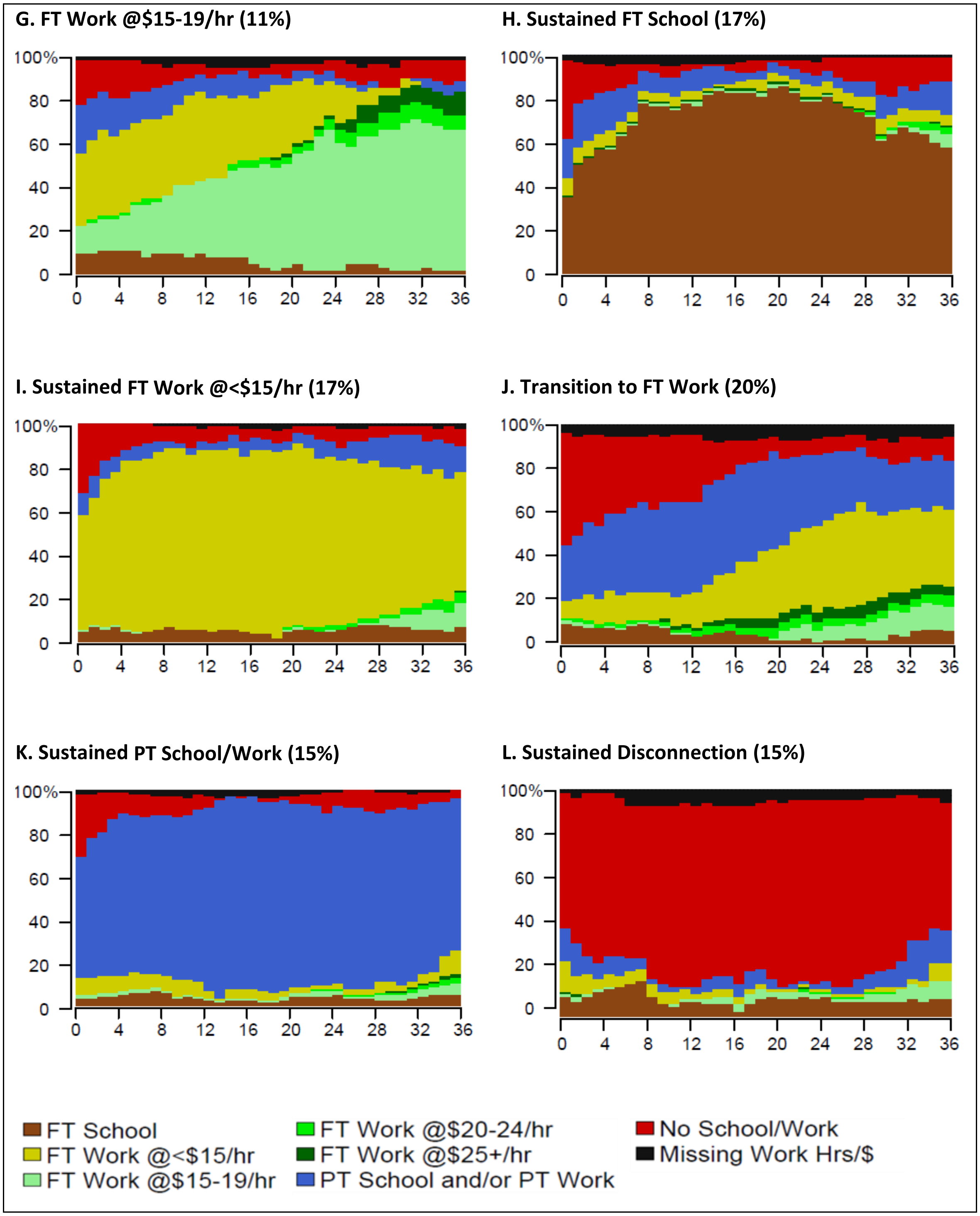
Note: Analyses in this table utilize data from baseline surveys administered at study intake, the three-year follow-up survey, the six-year follow-up survey (for measures of income, ability to handle a $400 emergency, and self-rated health), and college records obtained from the National Student Clearinghouse. Asterisks flag effects that are statistically significant: ***at the 1-percent, **at the 5-percent, *at the 10-percent level. Estimates for personal income are based on ordinary least squares regression, whereas the remaining estimates represent effects on odds from logistic regression models. All four models control for the full set of baseline characteristics shown in Table 2.

Figure 3: Percent in Various School-Work Statuses for Clusters Identified in the Treatment Group Sample (Showing Percent of Sample in Each Cluster in Graph Titles)



Notes: Shaded areas in each graph summarize the proportions of individuals in various school-work statuses each month over the 36-month follow-up period.

Figure 4: Percent in Various School-Work Statuses for Clusters Identified in the Control Group Sample (Showing Percent of Sample in Each Cluster in Graph Titles)



Notes: Shaded areas in each graph summarize the proportions of individuals in various school-work statuses each month over the 36-month follow-up period.