Career Trajectory and Health in Mid-Adulthood

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Abstract

Extant literature on the effects of socioeconomic status on health outcomes has two gaps: first, the dynamic measurement of socioeconomic status and status change is largely omitted; second, the causal relationship between the two factors suffers from selection bias. This paper tries to fill these two gaps by using sequence analysis to depict career mobility trajectories and applying propensity score methods (inverse probability weighting and propensity score matching) to address selection effects. Results based on the National Longitudinal Survey of Youth 1979 (NLSY 79) shows that upward career mobility tends to bring a premium in physical health, but not in mental health. Besides, cross-model comparisons show that not all of the association between career mobility and health outcomes can be attributed to selection effects. Although we still need to be cautious about the latter point, it does shed light on the causality issues involved in research on the interrelationship between socioeconomic status and health outcomes.

Keywords: Career Mobility, Physical Health, Mental Health, Sequence Analysis, Optimal Matching

Introduction

The effects of socioeconomic status (SES) on health outcomes have been documented by empirical studies from various disciplines. On the one hand, health inequality, in its own right, is a major concern for both scholars and the general public; on the other hand, health, as a major aspect of life chances, is deemed as a nonnegligible outcome of stratification in the social and economic system. Specifically, empirical studies have found that health outcomes are associated with a wide range of status indicators, including but not limited to family background (Mazzonna 2014, Warren 2016), education (Masters, Hummer and Powers 2012, Miech, Pampel, Kim et al. 2011, Sasson 2016), employment status (Burgard and Lin 2013, Kalousova and Burgard 2014, Tapia Granados, House, Ionides et al. 2014), income (Chetty, Stepner, Abraham et al. 2016, Qi 2012), and neighborhood characteristics (Browning, Wallace, Feinberg et al. 2006).

However, in the extant literature, there are two gaps that have not been fully addressed. First, although life course perspective is prevalent in research on the long-term effects of certain SES indicators on health outcomes, researchers tend to adopt a static approach to measure SES, using measures from a certain time point or a relatively short period; only a few of them (Nicklett and Burgard 2009, Willson, Shuey and Elder 2007) have tried to evaluate how changes in SES lead to health inequality. Second, the causality between SES and health are still under debate. Differentiation in SES is both a cause of health inequality and a consequence of previous disparities in health conditions (Burgard and Lin 2013, Conley and Bennett 2000, Currie 2009, Currie and Rossin-Slater 2015, Montez and Hayward 2014, Palloni 2006). Thus, the causal inference that SES affects health outcomes suffers from selection bias, because they may both result from early-life health conditions.

In this paper, we try to fill these two gaps by estimating the effects of career trajectory on physical health and mental health using data from the National Longitudinal Survey of Youth 1979 (NLSY 79). Our capability to fill these two gaps benefits a lot from recent development and innovation of methods in sociological research. For the first gap, the scarcity of using dynamic measures of SES, we use people's career mobility trajectories from 22 to 35 years old, which are depicted by sequence analysis, to predict health outcomes at 40 years old. Secondly, to reduce selection bias, we use propensity score matching and inverse probability weighting to reduce selection bias. Although we cannot claim that all of the selection bias is weeded out in our analysis, our results do lend support to the argument that not all of the association between SES and health is due to selection bias.

Data and Methods

The data we use in this paper are from NLSY 79. It is designed to provide a nationally representative sample of males and females who were 14 to 22 years old in 1979. The respondents were interviewed annually from 1979 to 1994, and biannually since then.

The dependent variables used in the analysis, health in mid-adulthood, are from the short-form 12-question (SF-12) summary scores in the 40-year-old health module. The NLSY 79 40-year-old health module provides two synthetic scores ranging from zero (lowest level of health) to 100 (highest level of health), one for physical health and the other one for mental health.

The key independent variable is constructed from the employment and job history data from wave 1979 to wave 2000. After 2000, NLSY changed their occupational classification codes from the 1970 census codes to the 2000 census codes, making it difficult for us to keep the measure for occupation consistent after wave 2000. To keep career mobility information comparable across respondents, we further restrict employment and occupation information used in the analysis to age 22 (the oldest age in 1979) to age 35 (the youngest age in 2000). In the analysis, the employment and job history data are synthesized into a variable of 4 categories: unemployed, professional/technical, managerial/administrative, and other.

The analysis proceeds in two stages. In the first stage, we conduct sequence analysis to identify major types of career mobility trajectories from 22 to 35 years old. Then, in the second stage, we use the major types identified from sequence analysis as the independent variable to evaluate health inequality associated with career mobility trajectory.

The sequence analysis in the first stage follows three steps. First, we array data into the person-week structure and construct a career trajectory (sequence) for each respondent. Second, we calculate the dissimilarity between sequences using the optimal matching algorithm (Abbott and Tsay 2000, Needleman and Wunsch 1970). The similarity between each pair of sequences is systematically determined by calculating the total "costs" of turning one sequence into the other one. To accomplish this transformation, there are two approaches: substitution and insert-delete (Abbott and Tsay 2000). In our study, the substitution costs are set as the transition rates between each pair of the employment/occupation states (Halpin 2017). The insert-delete cost is set as half the largest substitution cost so that the algorithms are prevented from using any more insert-deletes than enough to offset the difference in length (Abbott and Tsay 2000, Brzinsky-Fay, Kohler and Luniak 2006, Halpin 2017). Because for different respondents, the employment and job history data are from different calendar years, and the total number of weeks are slightly different from year to year, there is a small variation in sequence length. This variation in sequence length makes some pairs of sequences have a greater potential distance between them than do others. To correct this problem, we divide the ultimate cost of transformation by the length of the longer sequence within each pair (Abbott and Tsay 2000, Brzinsky-Fay et al. 2006). In the third step, we reduce the number of sequences into a few substantively distinct clusters, using the dissimilarity matrix obtained in the second step. We apply the dissimilarity matrix to cluster analysis based on Ward's linkage cluster analysis, which forms hierarchical groups of mutually exclusive subsets by maximizing the similarity within each subset (Ward Jr 1963). After trying different numbers of clusters, we end up with a 2-cluster solution, because it provides the most analytically meaningful prototypes. The sequence analysis is conducted by the SQ (Brzinsky-Fay et al. 2006) and SADI (Halpin 2017) packages in STATA.

In the second stage of the analysis, we use career clusters identified in sequence analysis as the independent variable to examine how health outcomes are differentiated by career trajectories. Because people's career trajectories may be affected by their previous health conditions, there is potential selection bias in our data. In the analysis, we use propensity score matching and inverse-probability weighting to address this problem. Variables used in the propensity score model include basic social demographic information, lifestyle, and previous health conditions from various waves of the survey. Table A1 in the Appendix reports results from the propensity score model.

Preliminary Results

Figure 1 shows the two career trajectory clusters identified from sequence analysis (sequence index plots). These plots show individual sequences over time. Individuals are arrayed along the y-axis, with each horizontal line representing one individual sequence. The x-axis is time:

in our case, the number of weeks since the age of 22. We use colors to indicate different job type or employment status.

The distinction between the two clusters is obvious. Although it is the same in the two clusters that most people started their career from neither professional nor managerial jobs, people in the two clusters ended up with different kinds of jobs in their early 30s. While in the first cluster, most people achieved upward mobility by moving into professional or managerial jobs, people in the second cluster seldom got a chance to hold these positions. Besides, people in the first cluster also tended to have less and shorter unemployed spells than those in the second cluster. In sum, the first cluster features upward mobility while the second cluster features no mobility or long-term unemployment.

Table 1 shows the estimated coefficients of career mobility cluster (Cluster 2 versus Cluster 1) on health outcomes. In the first model, we use career trajectory cluster as the only independent variable to estimate physical health and mental health scores. In this case, the coefficient reveals the differences in average health scores between the two clusters. According to results from this model (first row in Table 1), people in the second cluster, on average, score 2.315 points lower than those in the first cluster on physical health. On mental health, the second cluster scores .478 points lower than the first cluster, but the difference for mental health is not statistically significant. These results suggest that people who have experienced upward mobility hold a premium in physical health but not in mental health.

In the second model, we add control variables to the model. Similar to the first model, the second model also indicates that upward mobility is associated with an advantage in physical health but not in mental health (second row in Table 1). However, compared to the first model, the magnitude of the coefficient on physical health score in the second model drops from 2.315 to 1.493, implying that part of the effect we find from the simple regression model is caused by the confounding effects of the covariates.

In the last two models, we use propensity score methods to address the potential selection bias that the prospect of upward mobility and health outcomes at the age of 40 both result from previous health conditions. Results from the propensity score matching model (the third row in Table 1) and the inverse probability weighting model (the fourth row in Table 1) are both consistent with the regression models. Career mobility trajectory has a significant effect on physical health but not on mental health. Besides, compared to the second model (regression model with control variables), the magnitude of the coefficient on physical health increases from 1.493 to 1.503 and 1.775 respectively in the two propensity score models. This result lends support to the causal relationship between career trajectory and health outcomes. If all of the association between career cluster and health is attributable to selection effects, the effect of career mobility on health score should be reduced after part of the selection bias being addressed in the propensity score models. However, the results from our analysis suggest the opposite scenario. Career trajectory shows a greater effect in the propensity score models than in the OLS regression model. Thus, our results suggest that the association between career trajectory and physical health does not solely result from selection bias, but instead, part of the association should be attributed to a causal relationship between the two variables. However, because the results may be sensitive to model specifications, we need to be cautious about this finding and further test the sensitivity of the results.

Conclusion and Discussion

Our paper contributes to the understanding of how socioeconomic status affects health outcomes in two aspects. First, by using sequence analysis to delineate career trajectories, we are measuring SES from a dynamic perspective. Our results show that changes in SES have a significant effect on physical health but not on mental health. Compared to no mobility or long-term unemployment, upward mobility leads to a higher score on physical health in mid-adulthood. Second, our results suggest that there is a causal relationship between career mobility and physical health. After selection effects are partly accounted for by propensity score methods, career trajectory shows a stronger effect on physical health compared to what shown in the OLS regression model. However, we need to be cautious about this finding because it may be sensitive to model specifications.

In the next step, we are planning to refine our analysis in the following four ways.

First, we will further break down employment and occupation categories used in the analysis. At least, we will separate manual jobs from non-manual jobs in the "Other" category. The preliminary results show that mobility into managerial or professional positions brings a premium in physical health, but not in mental health. This may result from the distinction between manual and non-manual jobs. Thus, we expect transitions between manual and non-manual jobs to have a more salient effect on physical health than does mobility into managerial or professional jobs.

Second, we are going to incorporate mortality risk into our analysis as another outcome variable. As physical and mental health, the hazard of death is also deemed as an important aspect of life chances. Our current findings on the association between career trajectory and health outcomes indicate that it is worthwhile to test whether upward mobility also helps to lower the risk of death.

Third, we need to further adjust for selection bias. In the current analysis, we have addressed bias associated with selection into different career trajectory clusters. However, there is another kind of selection bias that we have not touched on in the current analysis. As Willson et al. (2007) suggested, research on health inequality suffers a lot from the disproportionate attrition and mortality of those with low SES. Thus, to get a valid evaluation of the causal relationship between career mobility and health outcomes, we need to account for the selection into death and attrition.

Last, we also need to test the sensitivity of our findings by implementing different model specifications. Our results suggest that part of the association between career trajectory and health can be attributed to a causal relationship. These results do shed light on the causality problem in health inequality research but the finding itself may be sensitive to model specifications. Although results from inverse probability weighting and propensity score matching are consistent in this regard, we still need to re-specify the propensity score model in different ways before we can reach any solid conclusion.

References

Abbott, Andrew and Angela Tsay. 2000. "Sequence Analysis and Optimal Matching Methods in Sociology: Review and Prospect." *Sociological Methods & Research* 29(1):3-33.

Browning, Christopher R., Danielle Wallace, Seth L. Feinberg and Kathleen A. Cagney. 2006. "Neighborhood Social Processes, Physical Conditions, and Disaster-Related Mortality: The Case of the 1995 Chicago Heat Wave." *American Sociological Review* 71(4):661-78.

Brzinsky-Fay, Christian, Ulrich Kohler and Magdalena Luniak. 2006. "Sequence Analysis with Stata." *Stata Journal* 6(4):435-60.

Burgard, Sarah A. and Katherine Y. Lin. 2013. "Bad Jobs, Bad Health? How Work and Working Conditions Contribute to Health Disparities." *American Behavioral Scientist* 57(8):1105-27.

Chetty, Raj, Michael Stepner, Sarah Abraham, Shelby Lin, Benjamin Scuderi, Nicholas Turner, Augustin Bergeron and David Cutler. 2016. "The Association Between Income and Life Expectancy in the United States, 2001-2014." *Jama* 315(16):1750-66.

Conley, Dalton and Neil G. Bennett. 2000. "Is Biology Destiny? Birth Weight and Life Chances." *American Sociological Review* 65(3):458-67.

Currie, Janet. 2009. "Healthy, Wealthy, and Wise: Socioeconomic Status, Poor Health in Childhood, and Human Capital Development." *Journal of Economic Literature* 47(1):87-122.

Currie, Janet and Maya Rossin-Slater. 2015. "Early-Life Origins of Life-Cycle Well-Being: Research and Policy Implications." *Journal of Policy Analysis and Management* 34(1):208-42.

Halpin, Brendan. 2017. "SADI: Sequence Analysis Tools for Stata." *Stata Journal* 17(3):546-72.

Kalousova, Lucie and Sarah A. Burgard. 2014. "Unemployment, Measured and Perceived Decline of Economic Resources: Contrasting Three Measures of Recessionary Hardships and Their Implications for Adopting Negative Health Behaviors." *Social Science & Medicine* 106:28-34.

Masters, Ryan K., Robert A. Hummer and Daniel A. Powers. 2012. "Educational Differences in US Adult Mortality: A Cohort Perspective." *American Sociological Review* 77(4):548-72.

Mazzonna, Fabrizio. 2014. "The Long-Lasting Effects of Family Background: A European Cross-Country Comparison." *Economics of Education Review* 40:25-42.

Miech, Richard, Fred Pampel, Jinyoung Kim and Richard G. Rogers. 2011. "The Enduring Association between Education and Mortality: The Role of Widening and Narrowing Disparities." *American Sociological Review* 76(6):913-34.

Montez, Jennifer Karas and Mark D. Hayward. 2014. "Cumulative Childhood Adversity, Educational Attainment, and Active Life Expectancy Among Us Adults." *Demography* 51(2):413-35.

Needleman, Saul B. and Christian D. Wunsch. 1970. "A General Method Applicable to the Search for Similarities in the Amino Acid Sequence of Two Proteins." *Journal of Molecular Biology* 48(3):443-53.

Nicklett, Emily J. and Sarah A. Burgard. 2009. "Downward Social Mobility and Major Depressive Episodes among Latino and Asian-American Immigrants to the United States." *American Journal of Epidemiology* 170(6):793-801.

Palloni, Alberto. 2006. "Reproducing Inequalities: Luck, Wallets, and the Enduring Effects of Childhood Health." *Demography* 43(4):587-615.

Qi, Yaqiang. 2012. "The Impact of Income Inequality on Self-Rated General Health: Evidence from a Cross-National Study." *Research in Social Stratification and Mobility* 30(4):451-71.

Sasson, Isaac. 2016. "Trends in Life Expectancy and Lifespan Variation by Educational Attainment: United States, 1990–2010." *Demography* 53(2):269-93.

Tapia Granados, José A., James S. House, Edward L. Ionides, Sarah Burgard and Robert S. Schoeni. 2014. "Individual Joblessness, Contextual Unemployment, and Mortality Risk." *American Journal of Epidemiology* 180(3):280-87.

Ward Jr, Joe H. 1963. "Hierarchical Grouping to Optimize an Objective Function." *Journal of the American Statistical Association* 58(301):236-44.

Warren, John Robert. 2016. "Does Growing Childhood Socioeconomic Inequality Mean Future Inequality in Adult Health?". *The Annals of the American Academy of Political and Social Science* 663(1):292-330.

Willson, Andrea E., Kim M. Shuey and Jr Glen H. Elder. 2007. "Cumulative Advantage Processes as Mechanisms of Inequality in Life Course Health." *American Journal of Sociology* 112(6):1886-924.

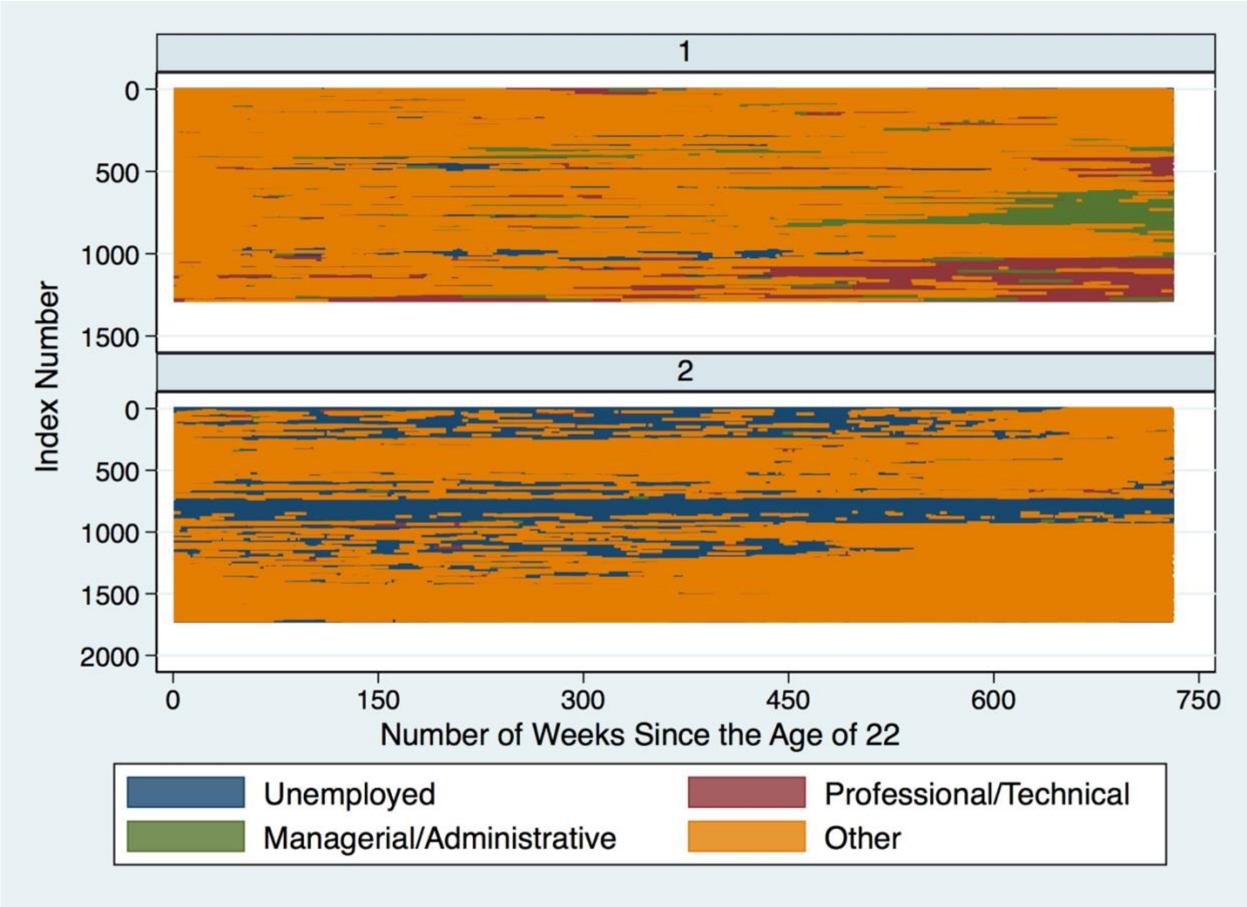

Figure 1: Sequence Index Plot of Career Trajectory Clusters, NLSY 79

Table 1: Estimated Coefficients of Career Trajectory Cluster (Cluster 2 vs Cluster 1) on Health Outcomes from Different Approaches, NLSY 79

	Physical Health Score		Mental Health Score	
Models	Coef.	S.E.	Coef.	S.E.
M1: OLS Regression without Control Variable	-2.315***	.335	-.478	.352
M2: OLS Regression with Control Variables [a]	-1.493***	.341	.139	.342
M3: Propensity Score Matching	-1.503***	.342	.050	.338
M4: Inverse Probability Weighting	-1.775***	.338	-.678	.361

Significance levels: *p<0.05, **p<0.01, ***p<0.001
Note: a. control variables in M2 are the same to independent variables in the propensity score model (Table A1).

Appendix

Table A1: Logit Model Predicting Career Trajectory Cluster for the Generation of Estimated Propensity Score, NLSY 79

Independent Variables	Coef.	S.E.
Gender (reference = male)		
Female	-.050	.082
Race (reference = white)		
Black	.593***	.094
Hispanic	.334**	.106
Living arrangement until 18 (reference = not with both parents)		
With both parents	-.083	.082
Family poverty status in 1979 (reference = not in poverty)		
Family in poverty	.516***	.100
Health insurance in 1989 (reference = having no health insurance)		
Having health insurance	-.524***	.101
Alcohol consumption in 1983 (reference = non-drinker)		
Drinker	-.346***	.085
Siblings (reference = have no sibling)		
Having at least one sibling	.099	.207
Depression in 1992	.058***	.010
BMI in 1985	.028**	.009
Constant	-.367	.334
Pseudo R^2	.064	
N	3,123	

Significance levels: *p<0.05, **p<0.01, ***p<0.001