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Risk Factors of Employment Transitions from Age 16 To 55 Years: A British Cohort Study

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Abstract:
Health, educational and socioeconomic status have been thought to be related to employment transitions in mid-life, but little is known about what the associations really are and how the associations change over time for British individuals. The purpose of this research is to investigate relationships between these factors and employment transitions for men and women in a British cohort. This paper uses the data set 1958 NCDS, and the method multiple imputation to impute the data, uses forward-backward stepwise regression to select variables and combine using average and weighted average to treat repeated measures. Lifetabe and Kaplan-Meier methods are used to show the distribution of duration to employment transitions. The discrete-time logit model of survival analysis is required to build the relationship between first employment, first unemployment and factors including health status, educational performance and socioeconomic background. Our findings suggest more attention should be paid to improve health conditions, educational levels and socioeconomic background of individuals before age 16, which could shorten the time to first employment and reduce the possibility to be unemployed.

Keywords: *Survival Analysis, Employment Transitions, Discrete-time, Repeated measures.*

I. INTRODUCTION

Employment is important for individuals to get access to resources and the extended social networks, and they could also be encouraged to participate in society (Ponomarenko,2016). The transitions from school to the workplace, and how to increase its efficiency, is a problem for researchers and policymakers. Claudia(2005) says becoming unemployed is associated with worsening physical and mental health. Higher level of education has beneficial effects on employment (Field,2000). It is plausible that these risk factors could be related to transitions in employment. It is important to investigate the associations since long-term unemployment is a waste of economic resources and one of the major causes of poverty and increasing inequalities Gunther(2003).

Survival analysis is widely used in studying the development prospect of individuals in social research and drug therapeutic effect in medical research. In modern society, people have to consider their economic, educational and health condition to prepare for the transitions in employment and stay competitive. Survival analysis could also help the country to improve the rate of employment and reduce the rate of unemployment, as well as to reduce gender inequality (Green,1999).

Educational system could meet the needs of society by learning the pattern of individuals' employment transitions.

Research has paid attention to the factors of employment transitions of young people who just finished their education (Russell and O'Connell, 2001). Some researchers considered interviewees' health, educational, economic background when those individuals are adolescents, while neglecting the changes after they become adults (Colless,1980). There is little evidence of the factors from different fields measured at different age that influences employment transitions over a long follow-up time.

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The lack of research in this area is mostly due to it requires longitudinal information and data which are difficult to collect and the research has to be followed up for a long time. Many researches that use survival analysis often use continuous time analysis, but it is more proper for this paper to use discrete time since the time of the event is measured in the nearest month in this data set. We only know the event occurred at which month interval, instead of precise time. However, in continuous-time model researchers assume that they know the exact time when the event occurs. If the time interval is short enough, the discrete-time model could be converted to continuous-time model (D'Agostino,1990).

In order to consider the effects at different age on employment transitions, this paper uses data 1958 NCDS to explore various risk factors including physical and mental health of those born in 1958 in Britain at age 16,23 and 33 years, performance at school, educational and socioeconomic background at age 7,11 and 16 years and study their effects on the timing of first employment and unemployment after age 16. This paper first select variables about these risk factors according to previous researches. However, this method of selection is subjective and there might be other variables that have effects on employment transitions but were not mentioned in other papers, so stepwise regression is used to help select variables systematically. Since the data has great part of missing values, we choose multiple imputation which could overcome the disadvantages of other methods like using average or simple regression for missing data. The variables are measured at different age, so we try different methods to treat repeated measures and find out combining average and weighted average of the measures is the best way. Discrete-time logit model is built to study the effects of variables selected on employment transitions. Because the model is based on Proportional Hazard Assumption, we add interaction variables by adding time multiplies initial variables and revise the model after testing the assumption.

II. Literature Review

Gender difference is an important effect on employment rates. Joshi (1996) reported that having children under age three reduced the possibility of females to be employed full-time greatly compared to males. OECD (2002) said that although the status of women has increased greatly, there is still a large gap between males and females since females are more responsible to care for the children and other family members.

Educational background plays an important role in further employment. Researchers focused on participation in learning, concluding that learning has beneficial effects on employment (Field,2000). Especially math score and reading score during age 7 and 16, Currie and Thomas(2015) reported that low reading scores and math scores are related to low possibility of employment using data NCDS. Jekins(2003) found learning was positively related to employment using a probit model among individuals in Britain. Their performance at school as children is also a key factor, individuals with poorer behavioral adjustment in childhood were more likely to experience unemployment in adulthood. But we can not infer that higher educational level must lead to reduce the time to the first employment and increase the time to the first unemployment, since the improvement of education level will also increase the expectation of higher income and higher status. The goal of employment is not only finding a job, but finding the job that individuals could agree with and accept.

The effects of health conditions on employment is also well-established. Lacey (2017) found weaker long-term ties to employment are related to greater increases in BMI through adulthood among British men and women. Case (2005) found out poorer health in adulthood are associated with a lower probability of employment and lower earnings in middle age since indiv might be in higher rate of absence. Researcher use self-reported health status at age 16, 23 and 33 years measured in NCDS, and

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consider several alternative models to analyse how physical influences the association between health and economic status as adults. As for mental health, psychological distress is associated with participants' status and high possibility of unemployment (Power,2005). Researchers measured mental handicap and emotional problems at age 16, 23 and 33 years, showing increased risk of psychological problems needing medical attention for unemployed men.

Factors related to socioeconomic background are also responsible for employment patterns (Macran,1996). Individuals who are unemployed are not distributed randomly, the people whose parents have low income and occupational reputation are more likely to suffer from unemployment.

However, although these researches chose similar variables with variables in this paper and studied the effects of these variables at different age on employment transitions using data 1958 NCDS, they selected variables subjectively without considering any systematical method. They just used the measures at different age directly and treated them as different variables, so the effects of some variables were not significant. Therefore, in this paper, we use stepwise regression to select variables systematically and combine using average and weighted average to treat repeated measures to overcome the obstacles in other researches.

Some researches use continuous-time survival analysis and build the cox model to study the factors that influence that influence employment transitions (Jekins,2002). It is not appropriate in this research since dates are recorded to the nearest month, but continuous-time model is based on precise time, therefore, we build discrete-time survival model.

III. Data

This paper uses the data The National Child Development Study (NCDS) which is a longitudinal survey of British people which were born in 1958. Participants were interviewed when they were born, 7, 11, 16, 23, 33, 42 and 54 years. The cohorts have collected information on social, health and socioeconomic aspects of participants' lives. Employment histories are also included, so we could track their employment transitions.

Variable description

The variables used in this study includes male, attendance, behavior problems, special education at age 7,11 and 16 years, reading score, math score, number of people living in the household, number of pupils at present on school roll,

$$BMI \ (\frac{weight(kg)}{height^2(m)}),$$

the age of parents leave school, tenure, do not like school, satisfaction of house, highest qualification at age 7 and 16 years, and health status, depression at age 16,23 and 33 years.

IV. Methodology

Variable selection

In this article, we choose measures according to the related literature subjectively and use the forward-backward stepwise regression systematically. There are forward selection, backward elimination, forward-backward regression in stepwise regression. But in forward selection, it can't reflect the change after new variables are selected in the model. The disadvantage of backward elimination is all independent variables should be included in the equation at first. So we use the last one(Steyerberg,1999). In this method, after we add new variables each time, we exclude the variables that are not significant, then select new variables.

Repeated measures

Some measures are measured at multiple waves. Previous research has considered multiple treatments of repeated measures. For example, Mensah(2008)

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considered using average directly, but it will neglect the different effects of measures as time changes. Jekins(2002) used all these variables independently, but some variables might not be significant since they might be highly related to others. This research uses these variables independently at age 7,11 and 16 years in the final model, From table1, we can find that some variables have similar coefficients at different age, so we use average of them. variables like reading score and math score have different coefficients at age 7 and 16, we use weighted average $0.2\times x_{age7}+0.8\times x_{age16}$. For variables at age 16,23 and 33 years, we use variables at age 16 only since over 90% event occurred before age 23.

Table1 Discrete-time logit model of duration and variables at different ages for repeated measures.

y	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
attend7	-0.1429	0.0326	-2.8500	0.0410	-0.1568	-0.0291
attend11	-0.1425	0.0418	-2.1800	0.0020	-0.2452	-0.1236
attend16	-0.1910	0.0722	-4.4100	0.0000	-0.4596	-0.1766
tenure7	-0.0686	0.0251	-2.7300	0.0060	-0.1179	-0.0193
tenure11	-0.0529	0.0272	-2.3200	0.0000	-0.2319	-0.9231
tenure16	-0.0674	0.0253	-3.5200	0.0000	-0.1386	-0.0394
reading7	0.0189	0.0123	2.0500	0.0400	0.0011	0.0493
reading16	-0.0864	0.0140	-7.1300	0.0000	-0.1271	-0.0723
math7	-0.0202	0.0113	-1.3300	0.0050	-0.0371	0.0072
math16	-0.0817	0.0144	-4.4600	0.0000	-0.0924	-0.0360
_cons	-1.5588	0.0127	-123.0200	0.0000	-1.5837	-1.5340

Multiple imputation

Missing values exist in this dataset. There are many methods for missing data. One is to delete the missing data. But in this way, we will lose much information. The other is using average, but it will reduce the variance of the data. If we use simple regression imputation, we use x to predict y, so we will increase correlation between x and y. Therefore, we choose multiple imputation. Multiple imputation deals with missing data (Royston,2004)related to all of the observed data. We use multiple imputation with 20 imputed data sets with all variables in the final model and variables including Parents want child to stay at school, age at start school and whether happy at school age 7 years , which have no missing values.

Event history analysis

This paper uses lifetable to show the distribution of the duration from age 16 to first employment and from first employment to first unemployment, which could reflect individuals' employment transitions in the time dimension. It also uses Kaplan-Meier method to compare the difference of duration from different groups,which estimates the survival function for duration.

The information in 1958 NCDS is sufficient to provide many factors like self-reported health conditions and experience of special education. The simplest model-the linear regression-could control the effects of variables on the response variable, but it could not cope with the censoring in data, which means some individuals have not experienced the event in the observation period.

Survival analysis (Allison,1984) could overcome the censoring problems. This paper models the hazard, using discrete-time logit model since dates are recorded to the nearest month. Using discrete-time analysis, we should restructure the data first. We should expand the data and add event indicator y_{ti} which could indicate whether the event occurs in time interval $[t,t+1)$. Then we calculate the discrete-time hazard function p_{ti} using $p_{ti}=P(y_{ti}=1\,|\,y_{t-1,i}=0)$, meaning the individual i experienced the event during interval t,but the event has not occurred before t. The discrete-time logit model is

$$\log(\frac{p_{ti}}{1-p_{ti}})=\alpha D_{ti}+\beta x_{ti}\ ,$$

where p_{ti} is the probability of the event during interval t, D_{ti} is the vector of functions of the cumulative duration by interval t, x_{ti} is a vector of covariates, α,β are coefficients. D_{ti} includes changes in p_{ti} with t.

The form of D_{ti} is $\alpha D_{ti} = \alpha_1 D_1 + \alpha_2 D_2 + ... + \alpha_q D_q$, where $D_1,...,D_q$ are dummies for the interval $t = 1,...,q$.

In this paper, the duration from age 16 to first employment and the duration from first employment to first unemployment is converted into dummies. For the event of first employment, the unit of each interval is six months, and if the duration is greater than ninety months, we group them in the fifteenth interval. As for first unemployment, the unit is one year, if the duration is greater than 360 months, it is group in the thirtieth interval.

Table2 Lifetable of first employment from age 16

Interval		Beg. Total	Deaths	Lost	Survival	Std. Error	[95% Conf.	Int.]
0	6	14734	666	0	0.9548	0.0017	0.9513	0.9580
6	12	14068	7087	0	0.4738	0.0041	0.4657	0.4818
12	18	6981	431	0	0.4446	0.0041	0.4365	0.4526
18	24	6550	1180	0	0.3645	0.0040	0.3567	0.3722
24	30	5370	277	0	0.3457	0.0039	0.3380	0.3533
30	36	5093	1311	0	0.2567	0.0036	0.2497	0.2638
36	42	3782	234	0	0.2408	0.0035	0.2339	0.2477
42	48	3548	401	0	0.2136	0.0034	0.2070	0.2202
48	54	3147	113	0	0.2059	0.0033	0.1994	0.2125
54	60	3034	227	0	0.1905	0.0032	0.1842	0.1969
60	66	2807	75	0	0.1854	0.0032	0.1792	0.1917
66	72	2732	582	0	0.1459	0.0029	0.1403	0.1517
72	78	2150	117	0	0.1380	0.0028	0.1325	0.1436
78	84	2033	427	0	0.1090	0.0026	0.1040	0.1141
84	90	1606	120	0	0.1009	0.0025	0.0961	0.1058
90	464	1486	1485	0	0.0001	0.0001	0.0000	0.0004

V. RESULT

The distribution of the duration to first full-time employment from age 16 are shown in Figure1.

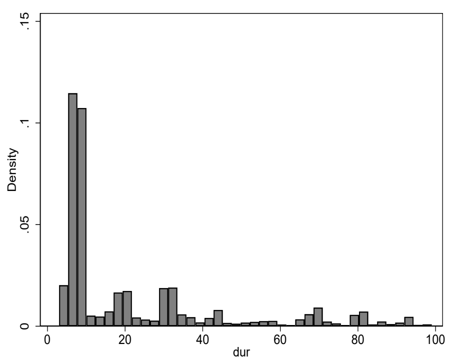

Figure1 Distribution of duration from age 16 to first employment

The horizontal axis represents the duration whose unit is one month. 394 individuals are censored, which means they did not experience first full-time employment until age 55. It shows that 50% of individuals get their first job in ten months after age16, and most of them get their first job during 7-10 months after age16. The researcher says around 50% people leave full-time education at age 17 from 1958 NCDS and 95% of them enter in full time employment in one similar research.

Table2 shows the possibility to get first full-time employment during each intervals. The length of each interval is six months. It shows that the possibility to find first job in 12 months is 0.5262. The median of the duration to find first job is between six to twelve months after age 16.

In the K-M method, it shows the survival curves of different groups from Figure2.

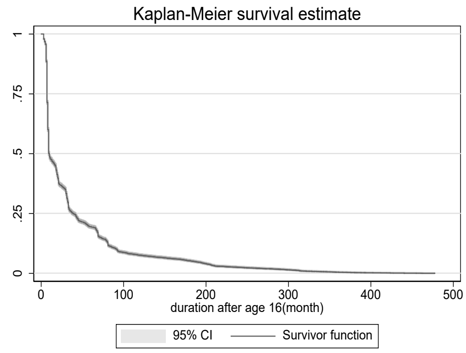

Figure2 K-M curve of first employment from age 16

The horizontal axis means the number of months from age 16 of individuals. The vertical axis shows the proportion of respondents who remained out of first full-time employment in each month. It can be seen that the median survival time was 10 months after age 16, which is consistent with the result from lifetable method. From Figure3, it shows that people with poor reading scores are more likely to find first job before age 16 plus 80 months(age 23),but after that, people with good reading scores are more likely to find firstjob.

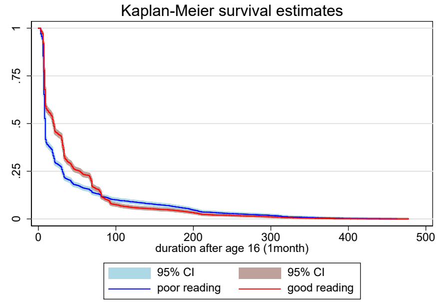

Figure3 K-M survival curve of firstemployment, by good reading score or poor reading score

From Fgure4, for those who passed A-level test at age 16,which means they will go to higher level of education, people with good reading scores are more likely to find first job after age 23. It suggests that both reading scores and educational achievement have effects on employment transitions. But this method does not control other factors like health conditions which may influence the employment transitions. Therefore, formal statistics model should be used to solve these problems.

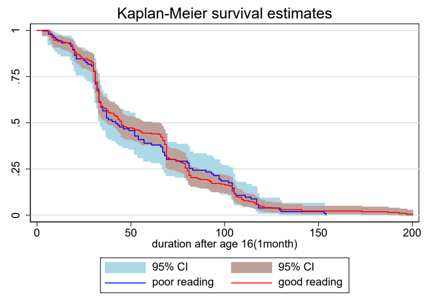

Figure4 K-M survival curve of first employment for those who passed A-level test at age 16, by good reading score or poor reading score

In the discrete-time model, effects on log odds are reported for each explanatory variables. The interval of time is six months, if duration is greater than 90 months, then we group them in t15. In the Table3, males could find first job earlier than females. The odds ratio(the ratio of finding first job to not finding first job) of males is 0.160 higher than females. Children who have experienced special education and have serious behavior problems and poor attendance find first job later. Those have poor physical, mental health at age 16 and abnormal BMI find first job later than others. Children whose family live in their own house and are satisfied with house could find first job earlier. Children have good reading scores and math scores and who like school and whose parents leave full time education later than others would find first job later and are more likely to enter university for further study. Previous research shows that good reading scores and math scores and high educational level of parents could increase the possibility to get employed (Currie, 1999). So the fact of this research may seem a little surprising, although it could be explained by those people are more likely to enter university for further education.

Table3 Discrete-time logit model of first full-time employment

y	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
t2	-0.7890	0.0307	-25.6700	0.0000	-0.8493	-0.7288
t3	-1.3168	0.0386	-34.0900	0.0000	-1.3926	-1.2411
t4	-1.7687	0.0477	-37.0500	0.0000	-1.8623	-1.6751
t5	-1.0690	0.0403	-26.5100	0.0000	-1.1480	-0.9900
t6	-1.2088	0.0455	-26.5900	0.0000	-1.2980	-1.1197
t7	-1.7864	0.0593	-30.1400	0.0000	-1.9026	-1.6703
t8	-2.2695	0.0751	-30.2300	0.0000	-2.4166	-2.1224
t9	-2.1921	0.0749	-29.2700	0.0000	-2.3389	-2.0453
t10	-2.6265	0.0931	-28.2000	0.0000	-2.8091	-2.4440
t11	-1.6036	0.0630	-25.4500	0.0000	-1.7271	-1.4801
t12	-1.2006	0.0581	-20.6700	0.0000	-1.3144	-1.0867
t13	-1.6626	0.0731	-22.7400	0.0000	-1.8059	-1.5193
t14	-1.1492	0.0647	-17.7500	0.0000	-1.2761	-1.0223
t15	-2.2593	0.0318	-71.0600	0.0000	-2.3216	-2.1970
male	0.1533	0.0197	6.9700	0.0000	0.0985	0.1756
special education	-0.1364	0.0971	-0.6100	0.0410	-0.2497	0.1309
behavior problem	0.0167	0.0372	0.7700	0.0430	-0.0443	0.1014
attendance	-0.2134	0.0329	-1.5700	0.0160	-0.1163	0.0127
parents education	-0.2790	0.0234	-11.9500	0.0000	-0.3248	-0.2333
BMI						
too light	-0.1905	0.0175	-10.8900	0.0000	-0.2247	-0.1562
too heavy	-0.2203	0.0518	-0.4700	0.0500	-0.3823	-0.5891
tenure	-0.1472	0.0213	-6.9100	0.0000	-0.1890	-0.1055
Health status	-0.0680	0.0171	-3.9800	0.0000	-0.1014	-0.0345
depression	-0.0549	0.0744	-0.7400	0.4600	-0.2006	0.0908
reading	-0.0624	0.0222	-2.8100	0.0050	-0.1059	-0.0189
math7	-0.0672	0.0107	-6.2500	0.0000	-0.0882	-0.0461
dislike school						
fair	-0.1366	0.0130	-10.5200	0.0000	-0.1620	-0.1111
not true	-0.0725	0.0162	-9.6700	0.0000	-0.5412	-0.1234
satisfaction of house						
fair	-0.0746	0.0166	0.4800	0.4300	-0.0246	0.0406
not satisfied	-0.2134	0.0329	-1.5700	0.0160	-0.1163	0.0127
_cons	0.5603	0.0652	8.5900	0.0000	0.4325	0.6881

Therefore, we rebulid the discrete-time model for those who passed the GCE A-level test at age 16. In the new logit model in Table4, for those who wanted to enter in further education, candidates who have good reading scores, math scores and whose parents

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are still in full-time education after age 16 could get first employment earlier.

Table4 Discrete-time logit model of first full-time employment for those passed A-level test

y	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
t2	-0.7773	0.0308	-25.2400	0.0000	-0.8377	-0.7170
t3	-1.2984	0.0387	-33.5600	0.0000	-1.3742	-1.2226
t4	-1.7464	0.0478	-36.5400	0.0000	-1.8401	-1.6527
t5	-1.0433	0.0404	-25.8200	0.0000	-1.1225	-0.9641
t6	-1.1841	0.0456	-25.9900	0.0000	-1.2734	-1.0948
t7	-1.7654	0.0593	-29.7500	0.0000	-1.8817	-1.6491
t8	-2.2491	0.0751	-29.9400	0.0000	-2.3963	-2.1019
t9	-2.1725	0.0750	-28.9900	0.0000	-2.3194	-2.0256
t10	-2.6070	0.0932	-27.9800	0.0000	-2.7897	-2.4244
t11	-1.5825	0.0631	-25.0900	0.0000	-1.7062	-1.4589
t12	-1.1805	0.0582	-20.3000	0.0000	-1.2945	-1.0665
t13	-1.6492	0.0732	-22.5400	0.0000	-1.7927	-1.5058
t14	-1.1402	0.0648	-17.5900	0.0000	-1.2673	-1.0132
t15	-2.2647	0.0319	-71.0700	0.0000	-2.3272	-2.2023
male	0.1721	0.0197	8.7400	0.0000	0.1335	0.2106
special education	-0.1035	0.0969	-1.0700	0.2860	-0.2934	0.0864
behavior problem	0.0238	0.0372	0.6400	0.5230	-0.0492	0.0967
attendance	-0.2206	0.0734	-3.0100	0.0030	-0.3644	-0.0767
parents education	0.2456	0.0236	10.4100	0.0000	-0.2919	-0.1994
BMI						
too light	-0.2010	0.0174	-11.5200	0.0000	-0.2352	-0.1668
too heavy	-0.2203	0.0518	-0.4700	0.0500	-0.3823	-0.5891
tenure	-0.1174	0.0212	-5.5400	0.0000	-0.1589	-0.0231
health status	-0.0026	0.0172	-0.1500	0.0090	-0.0311	0.3231
depression	-0.1314	0.0199	-6.5900	0.0000	0.0923	-0.0759
dislike school						
fair	-0.0725	0.0162	-9.6700	0.0000	-0.5412	-0.1234
not true	-0.1109	0.0131	-8.4600	0.0000	-0.1366	-0.0852
satisfaction of house						
fair	-0.0074	0.0167	-0.4400	0.6590	-0.0401	-0.0237
not satisfied	-0.0021	0.0329	-1.5700	0.0160	-0.1163	0.0127
reading	0.0724	0.0249	2.9100	0.0040	-0.1212	0.4660
math	0.1205	0.0123	9.8300	0.0000	-0.1446	-0.0832
_cons	0.3330	0.0679	4.9100	0.0000	0.2000	0.2398

In the model for first unemployment, children who have experienced special education, does not like school get first unemployment earlier in Table5.

Table5 Discrete-time logit model of first full-time employment

y	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
t2	-0.6435	0.0426	-15.1000	0.0000	-0.7270	-0.5600
t3	-0.7510	0.0452	-16.6100	0.0000	-0.8396	-0.6624
t4	-0.7157	0.0459	-15.5800	0.0000	-0.8057	-0.6256
t5	-0.6057	0.0457	-13.2600	0.0000	-0.6953	-0.5162
t6	-0.6228	0.0474	-13.1500	0.0000	-0.7157	-0.5300
t7	-0.6144	0.0487	-12.6200	0.0000	-0.7098	-0.5190
t8	-0.8605	0.0546	-15.7700	0.0000	-0.9674	-0.7536
t9	-0.9783	0.0585	-16.7200	0.0000	-1.0930	-0.8636
t10	-0.8955	0.0583	-15.3700	0.0000	-1.0097	-0.7814
t11	-0.9046	0.0601	-15.0600	0.0000	-1.0224	-0.7869
t12	-1.1560	0.0680	-17.0100	0.0000	-1.2892	-1.0228
t13	-1.2151	0.0712	-17.0700	0.0000	-1.3546	-1.0756
t14	-1.1637	0.0712	-16.3400	0.0000	-1.3034	-1.0241
t15	-1.1259	0.0717	-15.7100	0.0000	-1.2664	-0.9854
t16	-1.1560	0.0742	-15.5700	0.0000	-1.3015	-1.0105
t17	-0.9719	0.0705	-13.7900	0.0000	-1.1100	-0.8337
t18	-1.7428	0.1002	-17.4000	0.0000	-1.9391	-1.5465
t19	-1.7621	0.1024	-17.2100	0.0000	-1.9627	-1.5614
t20	-1.8514	0.1078	-17.1700	0.0000	-2.0626	-1.6401
t21	-1.8609	0.1095	-17.0000	0.0000	-2.0755	-1.6463

People have poor physical, mental health at age 16 and abnormal BMI at 16 get first unemployment earlier. It shows that Children's performance at school like behavior problems, reading scores and math scores does not have significant effects on first unemployment, but they are significant on first employment, which is similar to the result of Currie(2001). Physical and mental health, education level have important effects on both first employment and first unemployment. Sex is also v ery important on first employment and first unemployment.

In all, people should keep in good health and perform well and get higher education level in order to find job easier after graduation. Parents' economic and educational background also influence their children's employment transition.

Test for proportional hazard

The discrete-time logit model is based on proportional hazard assumption, meaning the effects of explanatory variables are constant across all time. But this assumption is not tenable all the time, so it is important to test if this assumption is reasonable or if interactions between covariates and time should be included. In this paper, the result of the test is the effects of variables including male, attendance, behavior problems, special education, reading score, math score, BMI, the age of parents leave school, tenure, do not like school, satisfaction of house, health status, depression are not constant across time (Figure5). Therefore, we add interactions between the time and these variables in the model.

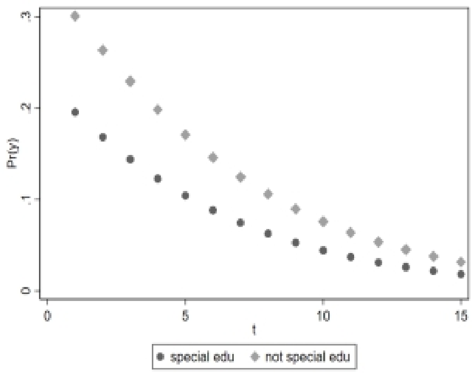

Figure5 Test for proportional hazard assumption

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VI. CONCLUSION

Focusing on employment transitions could help individuals to be more competitive in the workplace and improve the possibility to find jobs in a shorter period of time. This paper usesevent history analysis with British longitudinal dataset to study the association between educational, health, socioeconomic factors and first employment and unemployment transitions. The results contribute to the evidence that good health conditions, socioeconomic background and higher educational level could shorten the time to first employment and reduce the possibility to be unemployed.

Previous research has shown that poor mental health and physical health is related to lower possibility of employment transitions (Case,2005) and socioeconomic background are also responsible for the probability of employment (Macran,1996), which is similar to the results from this paper. But this paper extend first employment to both first employment and first unemployment, so it could better help people be prepared after being employed. Currie and Thomas(2015) reported that low reading scores and math scores are related to low possibility of employment. However, this research shows it is only true for those who passed GCE A-level test.

This research uses stepwise regression to select variables, and in the regression model, it uses least square estimation to estimate the coefficients. But if there are too many variables, there will be huge variance. There are many methods such as lasso and ridge regression to solve this problem, which could reduce the variance and mean square error. But these methods might increase the significance of the coefficients in the regression. The best way to select variables could be discussed in further study. In the future research, recurrent employment transitions could also be considered.

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