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Relationship Between Return to Experience and Initial Wage Level in United States

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Abstract: This paper estimates the relationship between return to experience and ini- tial wage on the basic of the latest dataset NLSY97 in the United States. In general, we will observe the relationship between return to experience and ed- ucational level is positive, while the relationship between return to experience and other unobservable individual abilities is negative when conditioning on educational attainment. In this case, I will divide the sample into four educa- tional groups and three ethnic groups. For each of these subgroups, I will use a linear model to estimate the relationship between initial wages and future wage growth. Also, I link my findings into some related theories to explain the negative relationship.

Keywords: Initial wage, Return to experience, Heterogeneity.

1. Introduction

It has been commonly acknowledged that earnings will rise with the accumulation of work ex- perience, which is easy to understand since we are much more likely to get higher wages when getting older and gaining more work experience. And also, people believe wage for work- ers with a higher educational level dominates that of workers with a lower educational level.

Mincer (1958) shows return to experience depends on some observable measures of permanent abilities for individuals such as educational level. Abowd (1999) introduced conditional meth- ods to estimate wage equations featuring both worker and firm fixed effects.

Although we observe the positive relationship above, there is some difference when we take future wage growth into account. It means that the relationship between future wage growth and individual educational level is positive, while the relationship between future wage growth and individual permanent abilities is negative. Thus, its widely recognized that including just education in wage regressions is not enough. We might suspect that return to experience also changes with some other unobservable abilities, which can be controlled for difference in per- manent abilities. Sorensen and Vejlin (2013b) makes a decomposition of the wage dispersion in the Danish labor market and estimates three different models: the standard AKM worker and firm fixed effects model, a fixed effect extension which includes an orthogonal match effect, and finally, a hybrid mixed effect model which also allows for a match effect that is correlated with the worker and firm effects. They decompose wages into observed and unobserved fixed effects for workers and firms, and find observable measures for abilities such as education only explain a small part of the variation in the estimated worker fixed effect.

There are some previous studies that have looked at this relationship. Gladden and Taber (2009) shows the covariance between the permanent component of wages and a random coeffi- cient on experience can be estimated from initial wages and later wage growth using the sample of NLSY79. Beker (1997) also uses a similar model and finds a negative covariance between wage growth and wage level in the PSID data. He first compares and evaluates the profile het- erogeneity model of earnings dynamics, in which the earnings/experience profile varies across individuals, to a competing model in which earnings has a unit root. And then provides new estimates of the variation in earnings growth rates using a twenty-year panel of earnings data for adult men drawn from the Panel Study of Income Dynamics (PSID) in United States. Glad- den and Taber (2009) only finds a small and negative effect between initial wages, which can be interpreted as individual ability level, and future wage growth, because they only focus on low-skilled workers and the dataset is not large enough.

Sorensen and Vejlin (2014) extends the identification argument developed by Gladden and Taber (2009) in order to non-parametrically estimate the relationship. Since in the two studies above, they both only estimate the covariance, while there is a potential problem that the rela- tionship between initial wage and future wage growth might not be linear. Sorensen and Vejlin (2014) uses a rich dataset in Denmark and divide the sample into four educational group to show whether the relationship is driven by some specific educational level. They first use a lin- ear model to estimate the covariance. Then they establish a non-parametric model and find that the relationship is not linear for those who have only a primary school or a high school degree and who have a master’s degree. Thus, covariance might not be a particular good estimator to describe the distribution in these cases.

There are also some related theories to explain this negative relationship between return to experience and initial wage. One explanation is provided by human capital theory. Mincer (1958, 1962) mentions the importance of investment in human capital on the personal income distribution. While on the job, workers will face a trade-off between earning wages and in- vesting in their own human capital in order to have higher wages in the future. Thus, workers with higher initial wages are much more likely to choose to earn wages rather than invest on themselves. In this case, we will expect a negative relationship between return to experience and initial wages.

Burdett and Mortensen (1998) provide a wage-posting model, where given the wages of- fered by all others and the distribution of worker reservation wage rates, the labor force avail- able to a specific employer evolves in response to the employer's wage. The higher the wage, the lager the steady-state labor force, because higher wage firms attract more workers from and lose fewer workers to other employers. Thus, more experienced workers and those with more tenure are more likely to be found in higher paying jobs. And there is a negative relationship between wage offers and quit rates across employers. It's easy to explain the negative relation-ship between return to experience and initial wages since its more difficult for those who are initially lucky to find a firm with high wages to find firms which are offering higher wages in the future. Postel-Vinary and Robin (2002) shows that high-productivity firms will be able to press workers start out with a lower wage, which actually enhances the negative relationship between return to experience and initial wages. The reason is that these workers have the potential of higher wages as they find other firms.

Sorensen and Vejlin (2014) also mention a third explanation based on unobserved productiv- ity and learning model, which is inspired by Jovanovic (1979). As the option value of keeping low-productive workers gets smaller over time, the workers will be fired. Hence the concave wage profile is driven by low-productive workers getting fired. They conduct some empirical tests in order to separate these different explanations. They also find some evidence that shows the productivity and learning model might be a part of the explanation and find no evidence in favor of the human capital theory and wage-posting model explanation.

This paper contains four sections. In the first section, I review some previous papers and show some related studies. In the second section, I will specify the linear wage model that would be used and the regression approach. In the third section, I will discuss the data used for the estimation and sample selection standards. Section four will show the empirical results and conclusion.

2. Econometric Approach

I will use a random effect linear model based on Sorensen and Vejlin (2014). My overall goal is to analyze the relationship between return to experience and initial wages through the relation- ship between initial wages and future wage growth. First, I will specify the wage expression. I assume that the wage structure is a linear function of individual-specific permanent ability, which can be represented as initial wage, and human capital, which can be measured as work experience. All year-specific effects have been removed from wages by detrended using an ordinary least squares (OLS) regression of year dummies on log wages. Thus, wages can be defined as:

$$w_{it} = \theta_i + \gamma_i E_{it} + \epsilon_{it} \tag{1}$$

Where θ_i and γ_i are worker-specific random effects, E_{it} is the experience of worker i at time t and ϵ_{it} is an error term. θ_i represents unobserved individual permanent abilities and γ_i represents unobserved individual return to experience.

We distinguish between two types of experience: potential experience and actual experience. Potential experience is initially set equal to zero and then simply grows one unit per year. Actual experience is an exact measure of experience accumulation each year, but is also set to zero when individuals entering the labor market. If the workers have worked full time all year, actual experience accumulation is equal to one unit. So, we won't take any internship or part-time jobs into account. According to previous studies, the experience-wage profile would be a concave on the full support, but would be very nearly linear during the first several years in the labor market.

The first restriction I will put on the sample is that only workers who have completed their highest education will be selected into the sample. I will assume workers won't have any work experience when entering the labor market, which means there would be $E_{i0} = 0$ as an as- sumption. This is also an important assumption for identification of random effects. Under this assumption, initial wage for individual i would be

$$w_{i0} = \theta_i + \epsilon_{i0} \tag{2}$$

And the wage growth from time $t - \alpha$ to t would be

$$\Delta_\alpha w_{it} = \gamma_i \Delta_\alpha E_{it} + \Delta_\alpha \epsilon_{it} \tag{3}$$

Where $\Delta_\alpha w_{it} = w_{it} - w_{it-\alpha}$, $\Delta_\alpha E_{it} = E_{it} - E_{it-\alpha}$, $\Delta_\alpha \epsilon_{it} = \epsilon_{it} - \epsilon_{it-\alpha}$. If I divide the right side and left side of equation (3) by the difference of experience $\Delta_\alpha E_{it}$, there will be an equation which expresses the wage growth normalized by the difference in experience $\frac{\Delta_\alpha w_{it}}{\Delta_\alpha E_{it}}$ as a function of the unobserved return to experience γ_i and an error term $\frac{\Delta_\alpha \epsilon_{it}}{\Delta_\alpha E_{it}}$.

$$\frac{\Delta_\alpha w_{it}}{\Delta_\alpha E_{it}} = v_i + \frac{\Delta_\alpha \epsilon_{it}}{\Delta_\alpha E_{it}} \tag{4}$$

According to equations (2) and (4), initial wage wi0 might be a good estimator for unobserved permanent ability θ_i, and wage growth normalized by difference in experience might be a good estimator for unobserved return to experience γ_i. So these two equations can be used to estimate the relationship between θ_i and γ_i.

It's obvious that we don't need to make any assumptions on the relationship between (θ_i, γ_i) and E_i, because actual experience would always be related with individual permanent abilities and individual return to experience. Also, Baker (1997) and Gladden and Taber (2009) find that the covariance between the error terms in equations (2) and (4) is tiny compared to the estimator and the potential bias is very small. Since I use a similar dataset and a similar method to esti-mate, I will simply disregard the negligible bias and consider the error terms to be uncorrelated.

By assumptions, θ_i and γ_i are both unobserved, we can only make use of equations (2) and (4). A simple OLS regression of wage growth normalized by difference in experience on initial wages would give us a slope coefficient that converges to

$$\frac{cov(w_{io}, \frac{\Delta w_{it}}{\Delta E_{it}})}{var(w_{io})} \tag{5}$$

According to the structure of equations (2) and (4), the slope coefficient above would converge to

$$\frac{cov(\theta_i \gamma_i)}{var(w_{io})} \tag{6}$$

So the covariance between unobserved permanent abilities and unobserved return to experience can be estimated using OLS regression.

3. Data and Sample Selection

This paper uses the National Longitudinal Survey of Youth (NLSY97) data to estimate the model specified above. The National Longitudinal Survey of Youth 1997 (NLSY97) is a survey of young men and women born in the years 1980-84 in United States. The NLSY97 consists of a nationally representative sample of approximately 9,000 youths who were 12 to 16 years old as of December 31, 1996. Selected youths would be interviewed every year. This survey started in 1997 and ended in 2013. The NLSY97 is designed to document the transition from school to work and into adulthood. It collects extensive information about youths' labor market behavior and educational experiences over time.

Table 1 describes individuals in NLSY97. Round 1 took place in 1997, while round 16 is the most recent data release, fielded in 2013-2014. We can see that 8984 individuals in total were initially interviewed in round 1. But only 80 percent (7141) of the round 1 sample were interviewed in round 16. And also, more than half of the interviewers are non-black or non- hispanic both in round 1 and round 16. In round 1, 25.99% interviewers are black and 21.16% are hispanic, while in round 16, only 12.76% remains to be black and only 10.33% are hispanic. And the percent of mixed-race interviewers remains to be 0.92% in the whole survey. I will disregard missing values and only select interviewers remaining in round 16 into the sample in this paper. The significantly decreasing number of black and hispanic interviewers makes me interested in relationship between initial wages and return to experience in race subgroups. So I will conduct OLS regression in each race subgroup and find whether the negative relationship is related with any specific race subgroups.

Table 1. Interviewers in NLSY97

	Black	Hispanic	Mixed	Non-black & Non-hispanic	Total
Round1	2335	1901	83	4665	8984
(%)	25.99	21.16	0.92	51.93	
Round16	911	738	66	3537	7141
(%)	12.76	10.33	0.92	75.99	

Table 2. Highest degree received for interviewers in round 16

	Non-degree	High school	Bachelor	Master	PhD
Round16	647	3960	1968	433	108
(%)	9.09	55.65	27.66	6.08	1.52

Table 2 describes the highest degree received for interviewers in round 16. More than half of the interviewers in round 16 have at most a high school diploma, 27.66% are educated at a bachelor's level, 9.09% don't have any degree and only less than 10% hold a master's or PhD degree. In each educational subgroup, I will also do OLS regression and find whether the negative relationship is related with any specific educational subgroups.

As for sample selection, I have some restrictions to narrow down the sample. First of all, I will only take full-time jobs into account and won't consider part-time jobs or internship or voluntary jobs as any kinds of experience accumulation. So only workers with full-time employment will be selected into the sample. If an individual is full-time employed in year X-1, but not in year X and again in years X+1 and X+2, then I will discard the wage growth relating to years X and X+1, but retain the wage growth relating to year X+2. Second, since NLSY97 only contains wage observations from 1997 to 2013, then I will only select individuals who have completed their highest education before 2010. Third, I will only take wages growth into account after individuals have completed their highest education. So all observations referring to periods before completion of highest education as well as observations during education will be deleted from the sample.

Table 3. Individuals in the sample

BlackHispanic Non-black & non-hispanic Total				
Individuals	800	780	2172	3752
(%)	21.32	20.79	57.89	

Table 4. Highest degree received for interviewers in the sample

Non-degree High school Bachelor Master PhD Total						
Individual	192	2026	1267	221	46	3752
(%)	5.12	54.00	36.77	5.89	1.23	

There are some advantages to use dataset from the NLSY97. Since I'm interested in indi- viduals' initial wages and wage growth in the first several years after entering the labor market, this requires that all individuals will be relatively young in the labor market. As NLSY97 has education and employment records for interviewers from school to work, it's relatively easy to get the information I need for wage regression. And individuals in the sample won't be too old to be selected.

Table 3 and Table 4 describe the sample I will use in the estimation. Similar with NLSY97, more than half of individuals in the sample are non-black or non-hispanic. And after sample selection, the number of mixed-race individuals becomes too small, so I just discard all mixed- race individuals from the whole sample. Also more than half of individuals in the sample obtained at most a high school diploma, 36.77% are educated at a bachelor level, 5.12% don't have any degree, 5.89% hold a master' degree and only 1.23% have get PhD.

Table 5. Descriptive statistics on initial wages and future wage growth

Non-degree High school Bachelor Master PhD										
	w_0	Δw	w_0	Δw	w_0	Δw	w_0	Δw	w_0	Δw
Mean	21357.97	1523.81	28996.23	2142.44	39975.99	2572.05	46134.38	4033.94	58061.26	18216.5
Std. dev.	14226.78	9838.24	19552.72	12051.57	25046.33	14665.14	24442.08	13705.42	40363.57	31184.55
P5	2000	-12000	4000	-14000	9000	-15000	10000	-14000	4000	-10000
P25	10000	-2000	16000	-2000	25000	-1000	31500	-250	33000	1500
Median	19800	0	26000	1000	36000	1500	45000	2000	50000	14000
P75	30000	4200	38000	6000	50000	7000	60000	8000	75000	20000
P95	46000	20000	60000	18000	80000	20000	80000	26000	130254	86002

Table 6. Descriptive statistics on initial wages and future wage growth

BlackHispanic Non-black & non-hispanic Full sample								
	w_0	Δw	w_0	Δw	w_0	Δw	w_0	Δw
Mean	27670.15	2232.4	30668.28	1701.75	36995.8	2930.01	33678.89	2564.34
Std. dev	18716.14	11708.3	18668.23	12772.26	25238.51	14360.33	23074.82	13486.71
P5	3000	-14000	5000	-15000	6000	-13898	5000	-14000
P25	14061	-2000	18000	-2000	20000	-1000	18016.5	-1500
Median	25000	1000	28850	1000	32000	1736	30000	1000
P75	38000	6750	40000	6000	47000	6150	44000	6000
P95	60000	20000	61500	20000	80000	20000	71500	20000

Table 5 and Table 6 show descriptive statistics for initial wages and wage growth by edu- cation and race. It's obvious that individuals with higher educational level have much higher initial wages and relatively higher wage growth. For race subgroups, black individuals have lower initial wages compared to hispanic individuals, while initial wages for non-black or non- hispanic individuals are significantly much higher. But the future wage growth for these three subgroups don't have many differences.

Table 7. Regression of log wage growth years 10-11 and 11-13 on initial wages, subsamples

	Non-degree		High school		Bachelor		Master		PhD	
Model	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
$(\frac{\Delta_{wit}}{\Delta E_{it}}, w_{io})$	-0.0796	-0.082	-0.0396	-0.0391	-0.0367	-0.0403	-0.0404	-0.0398	-0.0128	-0.0133
	(0.0277)	(0.0301)	(0.0143)	(0.0135)	(0.0174)	(0.0180)	(0.0266)	(0.0264)	(0.0917)	(0.0981)

Notes: Standard errors in parentheses are robust.

(1) mean unweighted regressions, (2) mean weighted regressions in which each individual has equal weights. All coefficients in the table have 5% significance level.

Table 8. Regression of log wage growth years 10-11 and 11-13 on initial wages, subsamples

	Black		Hispanic		Non-black & non-hispanic		Full sample	
Model	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
$(\frac{\Delta_{wit}}{\Delta E_{it}}, w_{io})$	-0.0624	-0.0721	-0.1032	-0.0925	-0.0152	-0.0213	-0.0313	-0.0378
	(0.0195)	(0.0201)	(0.0254)	(0.0135)	(0.0106)	(0.0180)	(0.0088)	(0.0064)

Notes: Standard errors in parentheses are robust.

(1) mean unweighted regressions, (2) mean weighted regressions in which each individual has equal weights. All coefficients in the table have 5% significance level.

4. Results

In this section, we present results from wage regression above. Table 7 and Table 8 presents the regression results for both potential and actual experience for each of the five educational subgroups and three race subgroups. Column (1) contains unweighted estimates of the slope and Column (2) contains weighted versions such that each individuals gets equal weight regardless if they appear once or twice in the sample. All subgroups show significant negative slopes and there are no significant negative differences between weighted regressions and unweighted regressions. It does make sense because I only use wage growth from 2010 to 2011 and from 2011 to 2013.

For educational subgroups, individuals with non-degree show the steepest negative covari- ances between initial wages and future wage growth, while individuals with PhD see the flat- test negative covariances. For race subgroups, hispanic individuals show the steepest negative covariances, followed by black individuals and non-black or non-hispanic individuals. And the coefficients will become more negative if I only use actual experience instead of potential experience together with actual experience, but there wouldn't be significant difference. All estimators in regressions are in the significance level of 5%.

From these results, we can estimate the negative relationship between initial wages and future wage growth both in full sample and subgroups. But as a result of limited dataset, I don't get significant estimators. And I also find the relationship is negative for all specific subgroups, but might be related with educational level, which implies that lower educational level has steeper negative relationship. And there is no obvious tendency for relationship in race subgroups, which should be estimated in a rich enough dataset.

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