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Do re-employment wages fall due to the depreciation of human capital or employer perceptions?

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Abstract

Using the data from the Survey of Income and Program Participation (SIPP) between 1996 and 2013, this study estimates the effect of unemployment duration on wages for workers between ages 25 and 64. The empirical strategy assumes a joint estimation of the job search and reemployment wage processes. The study also assumes the decomposition strategy of this effect into the human capital depreciation and stigma effects with the stigma effect refering to employers' perception that workers with longer duration of unemployment have lower productivity as compared to workers with shorter duration of unemployment. The results imply a substantial decline in the unemployment duration effect in the joint model relative to the OLS model. The main conclusion is that unemployment scarring can be mainly explained by differences in individual unobserved traits and to a lesser extent by human capital depreciation

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1. Introduction

The negative effects of job loss on future wages have been well-documented in recent empirical literature (Bernadette and Michaud 2017, Davis and von Wachter 2017, Johnson and Feng 2013, Couch et al. 2013). This paper empirically investigates the magnitude of workers' unemployment scarring, i.e. wage loss, attributable to the duration of recent unemployment using the 1996-2008 sample panel of U.S. workers drawn from the Survey of Income and Program Participation (SIPP). The unemployment scarring effect is estimated by decomposing it into the human capital depreciation and stigma effects. The human capital depreciation effect refers to the depreciation of worker's skills due to unemployment (Lazear 1976, Kiker and Roberts 1984, Edin and Gustavsson 2008). The longer a worker stays unemployed, the more his/her skills might depreciate. This would negatively affect the worker's future productivity, and thus, would lower his/her re-employment wage. The stigma effect (Heckman and Borjas 1980, Vishwanath 1989, Lockwood 1991) refers to employers' perception that workers with longer duration of unemployment have lower productivity as compared to workers with shorter duration of unemployment. The stigma effect also lowers the wages of workers with longer duration of unemployment.

A simple job search model that describes the problem faced by an unemployed worker is used to estimate the unemployment scarring effect. The model assumes that the unemployed worker receives a wage offer each period and compares it with his/her reservation wage (Mortensen 1986). Both reservation and offered wages can be decreasing functions of the duration of unemployment. In general, this suggests that the time of when a worker becomes employed and his/her re-employment wage are joint processes. To handle the simultaneity problem, Kiefer and Neumann (1979) suggest modeling a worker's job search behavior within a discrete-time binary choice framework, which is used in this study. A discrete-time binary choice model is estimated jointly with the re-employment wage process, which starts after accepting a job and is a function of the duration of recent unemployment.

For identification purposes, the set of restrictions excluded from the re-employment wage process that comprises a set of policy-related variables such as the state differences in generosity and duration of Unemployment Insurance (UI) benefits along with the size of the worker's household and the level of non-earned income is used. Compared to the benchmark method that ignores the simultaneity issue, this approach reduces the bias of the unemployment scarring effect by about 62%. In the empirical literature, the stigma effect is estimated through an interaction term, which combines unemployment duration and the current or lagged labor market conditions in the wage equation (Arulampalam 2001, Gregory and Jukes 2001, Mooi-Reci and Ganzeboom 2015). In this study, the decomposition of the scarring effect relies on two plausible assumptions: (i) the human capital depreciation effect is present for skilled workers but is nonexistent or negligible for unskilled workers and (ii) the stigma effect for skilled workers is greater or equal to stigma effect for unskilled workers. Based on these assumptions, this paper finds that a decline in re-employment wages amongst workers can be associated primarily with the human capital depreciation effect and with lesser extent with stigma effect. However, the effect is not statistically significant at the most conventional levels. Hence, this paper concludes that unobserved worker heterogeneity mainly explains workers' unemployment scarring, i.e. wage loss, which is

attributable to the duration of recent unemployment. Thus, a more motivated worker has a lower duration of unemployment and higher reemployment wages than his/her counterpart.

2. Model, Data and Decomposition

2.1. Empirical Model

The model's starting assumption is that the unemployed worker *i,* who resides in state *s* in period *t*, receives a job offer noted as wage, W_{ist}^{o}, and compares it with his/her reservation wage of W_{ist}^{R}. The worker accepts this job offer if $W_{ist}^{o} \geq W_{ist}^{R}$ and otherwise, rejects it and continues his/her search in period *t+1*. The worker's offered wage in the natural log, W_{ist}^{o} is a function of a worker's current duration of unemployment, D_{ist}; worker characteristics, X_{ist} such as race, age, marital status, gender, education, and metropolitan area status; an indicator of unskilled occupation in the previous job, $UNSKIL_{ist}$; an interaction of the duration of unemployment with the unskilled occupation dummy, $UNSKIL_{ist} \times D_{ist}$; year, α_t^o and state, ϑ_s^o fixed effects; worker's unobserved heterogeneity, μ_i^o; and the random error, v_{ist}^o:

$$W_{ist}^{o} = X_{ist}\beta^{o} + \theta_1^{o} D_{ist} + \theta_2 UNSKIL_{is} + \theta_3 UNSKIL_{ist} \times D_{ist} + \alpha_t^{o} + \vartheta_s^{o} + \mu_i^{o} + v_{ist}^{o}. \quad (1)$$

The worker's reservation wage in the natural log, W_{ist}^{R}, is a function of the same worker-level characteristics, X_{ist}, some factors (discussed in the next subsection) that directly affect the reservation wage without a direct impact on the offered wage, Z_{ist}, current duration of unemployment, D_{ist}, year, $\alpha_{t,}^{R}$ and state, ϑ_s^{R}, fixed effects, worker's unobserved heterogeneity, μ_i^{R}, and the random error, v_{ist}^{R}

$$W_{ist}^{R} = X_{ist}\beta^{R} + Z_{ist}\delta + \theta_1^{R} D_{ist} + \alpha_t^{R} + \vartheta_s^{R} + \mu_i^{R} + v_{ist}^{R}\ . \quad (2)$$

The decision rule of accepting a job offer is a binary discrete-time choice process given by the difference between the reservation and offered wages. Thus, the probability of re-employment at any time is described by:

$$P(h_{it} = 1) = P(W_{ist}^{o} - W_{ist}^{R} \geq 0) =$$
$$P\left(-\tilde{v}_{ist} < X_{ist}\tilde{\beta} + Z_{ist}\tilde{\delta} + \tilde{\theta}_1 D_{ist} + \tilde{\theta}_2 UNSKIL_{ist} + \tilde{\theta}_3 UNSKIL_{ist} \times D_{ist} + \tilde{\alpha}_t + \tilde{\vartheta}_s + \tilde{\mu}_i\right) \quad (3)$$

In Equation (3), F is the cumulative distribution function of $-\tilde{v}_{ist}$ and is approximated with the logistic response function. The estimated job search process outlined in Equation (3) is a stacked logit function with a set of time-specific intercepts, which captures the effect of duration dependency on the search length for a job. The empirical strategy jointly estimates Equations (1) and (3) assuming M points of support in order to approximate the distribution of μ. Since there are two equations in the model, μ consists of two vectors with each representing the set of individual

unobserved heterogeneity parameters in each of the equations. Conditional on the mass point, $\mu_m = (\mu_{1m}, \mu_{2m})$, worker i's contribution to the likelihood function is as follows:

$$A_{im}(\mu_m) = \prod_{t=1}^{D_i} P(h_{it} = 1 \mid h_{it-1} = 0, \mu_{1m})^{h_{it}} (1 - P(h_{it} = 1 \mid h_{it-1} = 0, \mu_{1m}))^{1-h_{it}} \prod_{l=D_i}^{T} f(W_l \mid \mu_{2m}) \quad (4)$$

The unconditional contribution of worker *i* is:

$$A_i = \sum_{m=1}^{M} \varphi_m A_{im} \quad (5)$$

with φ_m being a weight of mass point μ_m. The likelihood function can now be written as follows:

$$L = \prod_{i=1}^{I} A_i \quad (6)$$

The likelihood function is maximized with respect to all parameters as well as the individual's specific mass points and weights. In each equation, a constant term is included and is normalized to the individual mass point per equation to zero in order to identify the model. For the covariance matrix, a robust covariance matrix is used.[1]

Identification of the duration effect is secured through theoretical exclusion restrictions included in vector Z_{ist}, which are factors that directly affects an individual's reservation wage, thus, worker's job search behavior. For the sake of identification, vector Z_{ist}, includes the average potential duration along with the average replacement rate of UI benefits in worker's state of residency. More generous and prolonged UI benefits have positive impacts on reservation wage reducing the chance of reemployment. Also, two worker-level variables, that directly impact the duration of unemployment such as the size of the worker's household and the level of non-earned income are included in vector Z_{ist}.

2.2.Data

This study uses four panels of SIPP, which originate in 1996, 2001, 2004, and 2008. SIPP is a set of household–based longitudinal surveys of non-institutionalized individuals residing in the continental U.S. A number of unemployed respondents experienced more than one incidence of unemployment, all incidences are included in the analytical sample. In total, there are 29,160 incidences of unemployment for workers aged 25 – 64 years between January 1996 and July 2013.

The respondent's occupation prior to becoming unemployed is used to identify whether the respondent is a skilled or an unskilled worker. Regarding the classification of occupations, the approach used by the Social Security Administration (SSA) in determining skill requirements for disability benefit applicants is used. Specifically, "unskilled work is work, which needs little or no judgment to do simple duties that can be learned on the job in a short period of time" (Social Security, n.d.).[2] With respect to the unskilled occupation, the worker does not acquire any work skills and therefore, any worker can learn how to do the unskilled job within 30 days (Social

[1] The Fortran code used to estimate the discrete factor model is kindly provided by Professor David Guilkey of the University of North Carolina, Chapel Hill.

[2]Retrieved from http://www.ssa.gov/OP_Home/cfr20/416/416-0968.htm, 01/08/2015.

Security, n.d.). Table 1 reports descriptive statistics for key variables used in the analysis. Slightly greater than 19% or 5.656 workers in the sample can be classified as unskilled workers and descriptive statistics show the unskilled workers are qualitatively different from their counterparts in many dimensions.

Table 1. Descriptive Statistics

Variables		All (N=29,160)	Skilled (N=23,504)	Unskilled (N=5,656)
White		79.9%	81.2%	74.4%
Age:	25-35	26.7%	25.9%	29.9%
	35-45	27.0%	27.0%	27.2%
	45-62	37.6%	38.2%	35.1%
	Above 62	8.6%	8.8%	7.9%
Married		60.5%	62.5%	52.0%
Male		45.7%	46.3%	43.3%
Education:	Below HS	13.3%	10.0%	26.9%
	HS diploma	28.8%	26.7%	37.5%
	Some College	50.2%	54.0%	34.4%
	College +	7.7%	9.3%	1.3%
Lives in Metropolitan Area		84.7%	85.4%	81.9%
# of Individuals in Household		3.1 (1.6)	3.0 (1.5)	3.3 (1.8)
Non-earned income		1,005 (2,800)	1,100 (2,972)	609 (1,881)
State UI potential duration		23.6 (2.1)	23.6 (2.1)	23.6 (2.1)
State UI Replacement Rate		34.8%	34.8%	34.6%
Duration of Unemployment		9.0 (10.6)	8.9 (10.5)	9.4 (11.1)
Unskilled worker		19.4%	0.0%	100.0%
Reemployment Wage		17.2 (34.8)	18.4 (36.0)	11.4 (27.9)

2.3. Decomposition of Human Capital Depreciation and Stigma Effects

The identification of two effects relies on two simple assumptions: (i) unskilled workers do not experience human capital depreciation during unemployment and (ii) the stigma effect for skilled workers is greater or equal to the stigma effect for unskilled workers. While an unskilled worker might experience some depreciation of skills due to work interruption, the skills depreciation can be smaller in magnitude than the skilled counterpart (Neumann and Weiss 1995, Gorlich and de Grip 2009). For example, Neumann and Weiss (1995) provide both theory, and then empirical evidence, that a high-skilled worker may experience greater human capital depreciation because of stronger exposure to technological change. Thus, during the period of unemployment, work skill requirements of a skilled worker may change substantially due to more of an intensive adoption of new technology at the workplace. Furthermore, the unskilled worker's human capital depreciation can be more easily reversed in a short amount of time compared to the skill depreciation of a skilled worker.

In Equation (1), the primary parameters of interest are θ_1^o and θ_3. The monthly wage penalty faced by a worker is a combination of the stigma effect, γ_j and the actual human capital depreciation effect, d_j where j is either skilled (s) or unskilled (u) worker. If the estimate of unemployment scarring is unbiased for the skilled worker, then $\gamma_s + d_s = \theta_1^o$. With the above two assumptions, the effect for the unskilled worker is represented solely by the stigma effect, $\gamma_u = \theta_1^o + \theta_3 \leq \gamma_s$. Specifically, if the stigma effect for unskilled workers is the lower bound of the stigma effect for skilled workers, then θ_3 identifies the penalty, which the skilled worker may face for each month of unemployment due to human capital depreciation, $-d_s = \gamma_s - \theta_1^o \geq \gamma_u - \theta_1^o = \theta_3$.

3. Results

Table 2 presents the coefficients from the reemployment wage equation (Equation 1) for the Ordinary Least Square (OLS) and joint models. Results from the joint model show that the total effect of unemployment duration on re-employment wages is -0.005, which infers that each month of unemployment, reduces re-employment wages by 0.5%. The coefficient corresponding to the human capital depreciation effect, θ_3, has the same magnitude as the total effect and thus the given effect explains primarily the decline in reemployment wages because of duration of unemployment after properly addressing endogeneity of the duration of unemployment in the reemployment wage equation. However, the estimated coefficients are both not statistically significant at the 10% level. Hence, it appears that unemployment scarring in re-employment wages can be explained to a larger extent by unobserved worker heterogeneity and to a lesser extent by human capital deprecation or stigma effects. Although the simpler OLS model, shows that the reemployment wage may decline by 1.3% per month of unemployment and almost half of this decline, 0.6% can be explained by the human capital depreciation effect and 0.7% by the stigma effect.

Comparing the key point estimates across the models, it is determined that the total duration effect is reduced by 62% after controlling for worker's unobserved heterogeneity in the re-employment wage equation. In the OLS model, the point estimate should be biased upward since a worker's unobserved heterogeneity such as a worker's motivation is not taken into account. Assuming *ceteris paribus*, if a more motivated worker experiences a shorter duration of unemployment and is paid more than a less motivated counterpart, then the OLS over-estimates the total duration effect due to the presence of this important latent variable in the wage process. Therefore, the more complex model provides a substantial reduction in the point estimates that is consistent with theoretical expectations, the employed estimation procedure should reduce the bias if not completely eliminate it. Compared to the results of the more complex model, the unemployment scarring is primarily explained by unobserved worker heterogeneity. A more motivated worker searches for jobs more intensively and finds a higher paid job and the outcome of reemployment is neither affected by skill depreciation nor employer discrimination on a basis of duration of unemployment.

Regarding the identification strategy, it should be noted that the coefficients corresponding with the exclusion restrictions all have the expected signs in the reemployment equation. The longer and more generous UI benefits, along with the higher non-earned income, reduce the chance of reemployment, thus, increasing the duration of unemployment. The size of household intensifies the job search, which leads to quicker reemployment and lower duration. The likelihood ratio test

reported in Table 2 confirms substantial explanatory power of exclusion restrictions in the reemployment equation.

Table 2. Empirical Results

	OLS		Joint Model			
	Wage Equation		Wage Equation		Reemployment Equation	
Variable	Coeff.	SE	Coeff.	SE	Coeff.	SE
White	0.065	0.014	0.057	0.025	0.156	0.020
Married	0.109	0.011	0.084	0.018	-0.115	0.017
Male	0.209	0.011	0.171	0.023	0.343	0.016
Lives in metropolitan area	0.096	0.012	0.013	0.016	0.021	0.019
Unskilled	-0.285	0.018	-0.312	0.028	-0.094	0.055
Age (Reference group = 25-35)						
35-45	0.044	0.013	0.056	0.019	-0.017	0.020
45-62	0.042	0.013	0.055	0.020	-0.355	0.021
Above 62	-0.069	0.032	-0.026	0.043	-1.380	0.043
Education (Reference group = below HS)						
High School diploma	0.176	0.017	0.134	0.030	0.036	0.026
Some College	0.378	0.016	0.309	0.024	0.207	0.025
College +	0.791	0.028	0.759	0.049	0.442	0.037
Exclusion Restrictions						
# of individuals in household					0.015	0.005
Non-earned income					-0.090	0.012
State UI potential duration					-1.210	0.374
State UI Replacement Rate					-0.012	0.011
Parameters of Stigma and Skill Deprecation						
Duration of Unemployment	-0.013	0.001	-0.005	0.004		
Duration X Unskilled	0.006	0.002	0.005	0.004		
Constant	1.922	0.044	0.152	0.069	-3.556	0.395
Mass Point $\mu 1$ ($\psi 1$=0.041)			0.000	0.000	0.000	0.000
Mass Point $\mu 2$ ($\psi 2$=0.058)			3.048	0.076	0.471	0.139
Mass Point $\mu 3$ ($\psi 3$=0.428)			1.799	0.067	0.196	0.085
Mass Point $\mu 4$ ($\psi 4$=0.219)			1.247	0.060	0.095	0.076
Mass Point $\mu 5$ ($\psi 5$=0.254)			2.325	0.071	0.311	0.117
Value of Likelihood Function	-244556.4					
Likelihood Ratio Test	146.3					

Note: The OLS estimates are from the wage equation, Equation (1). The coefficient estimates are jointly estimated from the wage equation with the process approximating the duration of unemployment. The standard errors are obtained by clustering over individuals' robust standard errors. The mass point 1 is normalized to 0. As has been previously stated, the empirical models also include state and year fixed effects, which are available upon request.

4. Conclusion

This paper shows that based on the simple model, one month of unemployment may decrease the re-employment wages of skilled workers by 1.3% and of this decline, 0.6% can be explained by skill depreciation and 0.7% by stigma effect. However, the identification strategy used in this study, shows that these effects are significantly biased upward due to the failure to account for unobserved worker heterogeneity. In the more complex model, the total duration effect is reduced by 62% and is statistically insignificant. This leads to a conclusion that unemployment scarring can be explained by differences in individual unobserved traits and not by human capital depreciation or employer discrimination.

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