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Effect of Informal Training on Skill Levels of Manufacturing Workers*

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Abstract Using self-reported data on training and productivity in 'Human Capital Corporate Panel' and employing a bivariate probit model that has a dynamic aspect, we were able to estimate skill level depreciation rate and effect of both formal and informal trainings on skill accumulation. Average annual depreciation rate of skill level was estimated to be 24%. Both formal and informal trainings were estimated to be effective in skill accumulation.

Keywords Informal training, skill accumulation and depreciation, bivariate probit model, simulated maximum likelihood estimation

JEL Classification J01, C13, C24.

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1. INTRODUCTION AND LITERATURE REVIEW

There are two types of training in workplace: formal and informal trainings. Formal training, also called ‘off-the-job training’, refers to a systematic learning process conducted through formal, possibly vocational, educational institutes. Formal training, especially when it is provided by training specialists, usually has similar contents among different firms. The term ‘informal training’, also called ‘on-the-job training’, refers to a learning process of workers that takes place while doing their own jobs(‘learning-by-doing’) or by watching their colleagues’ work(‘peer-learning’). As the name suggests, informal training is largely unintentional, unsystematic, highly flexible, and firm- or job-specific.

Such firm-specific knowledge coupled with the fact that informal training is virtually costless compared to formal training implies that it can be an effective way of improving worker’s productivity. According to research, about 2/3 of U.S. workers are engaged in informal training (Altonji and Spletzer (1991)). Nonetheless, most economic researches on workplace training have focused on formal training likely because of invisible nature of informal training.[1] Ignoring the effect of informal training, however, can bias the effect of formal training on productivity. For example, Weiss (1994) reported that effects of formal training was overestimated when that of informal training were ignored due to complementarity of formal and informal trainings.

Effects of training on skill accumulation and productivity is based on human capital theory. Both formal and informal trainings are an investment in human capital and accumulate human capital stock. So we may model the accumulation of human capital process as follows.

$$HC_{i,t} = (1-\delta)HC_{i,t-1} + TR_{i,t}$$

where $HC_{i,t}$ stands for individual i’s stock of human capital at time t, and $TR_{i,t}$ stands for training acquired during time period t. The δ captures depreciation in human capital that may happen because of various reasons.[2] The $HC_{i,t}$ de-

[1] The ‘informal training’ or more precisely ‘informal leaning’, also called as ‘incidental learning’, has been studied for long in education. See Marsick and Watkins (1990), Watkins and Marsick (1992), and recently Eraut (2004) and references therein for more information. Although relatively less frequent, the impact of ‘informal training’ on productivity or wage has been also studied in economics. See Liu and Batt (2007) for example.

[2] One of reasons for the depreciation is umemployment. See Kunze (2002), for example. This reasoning of skill depreciation does not work for our case because we want to allow for skill level depreciation even without unemployment of individual worker. There may be other reasons for skill depreciation. For example, McFadden (2008) argues individual’s cognitive skill may depreciate because acquired knowledge is forgotten or becomes obsolete.

termines marginal productivity of labor (MPL) and MPL equals to wage rates in the equilibrium. Therefore in empirical studies for effects of informal training on productivity, Mincerian models may be used with tenure as a proxy for amount of informal training and a functional form of your choice for f.[3]

Thanks to our data, however, we took a rather different approach. Our data has an advantage of having direct measures of worker's skill level and self-evaluated informal training level for both 'peer-learning' and 'learning-by-doing'. We described our data and model in next section.

2. ECONOMETRIC MODEL AND DATA

The data we used is 'Human Capital Corporate Panel(HCCP)' available from Korea Research Institute for Vocational Education and Training (KRIVET). It is a panel survey that collects data from corporates every two years since 2005.[4]

Readers may want to be cautious here. The HCCP is a panel survey at corporate level but repeated cross sectional at individual worker level which we used for our study.

Although the data we used were cross sectional, we were able to use information of two distinct time periods in our model as if we used panel data. It was made possible because of particular questions in the HCCP. In the HCCP questionaire, there were two questions about manufacturing worker's skill level: skill level at the time of hire(y_0 in our model); skill level at the time of survey(y_1 in our model). We developed a model, which we described later, that utilized these two pieces of information in order to investigate effects of informal training on skill improvement.

Manufacturing worker's skill levels were categorized in seven: (1) unskilled simple manual labor (*dansunnomujik* in Korean); (2) apprenticeship (*gyeonseupgong* in Korean); (3) semi-skilled level 1 (skillful for one machinery or production functionality, *danneunggong* in Korean); (4) semi-skilled level 2 (very skillful for one machinery or production functionality, *danneungsukryeongong* in Korean); (5) skilled level 1 (skillful for multiple machinery or production functionalities, *daneunggong* in Korean); (6) skilled level 2 (very skillful for multiple machinery or production functionalities, *daneungsukryeongong* in Korean); (7) highly skilled (not only skillful in multiple machinery and production functionalities but also knowledgable in comprehensive production process,

[3]For example, Frazis and Loewenstein (2005) used a log-log linear model.

[4]General information for the data and downloadable website can be found at https://www.krivet.re.kr

Table 1: Reported Skill Levels: $\Pr[y_0, y_1]$

	$y_1 = 1$	$y_1 = 2$	$y_1 = 3$	Sum
$y_0 = 1$	0.085	0.391	0.233	0.708
$y_0 = 2$	0	0.130	0.120	0.250
$y_0 = 3$	0	0	0.042	0.042
Sum	0.085	0.520	0.395	1 (N=2,765)

gisuljeok daneunggong in Korean).[5] In the estimation, we simplified the hierarchy to three levels: level 1 = (1)+(2); level 2 = (3)+(4)+(5); level 3 = (6)+(7). Of total 3,400 manufacturing workers participated in the 2011 survey, we used data of those who began working at current (as of 2011) position from year 2010 or earlier. In the end, we used 2,765 observations. The reported skill levels and variation over time is in the table 1.

The time gap between the time of hire and time of survey (which is tenure measured in 10 years and denoted by T in our model) differs individual to individual. The table presents estimated joint probability $\Pr[y_0 = r, y_1 = s]$, where $r, s \in \{1,2,3\}$ being one of the skill levels 1, 2, or 3. It reads, for example, 8.5% of surveyed individuals reported they remained at skill level 1. As seen, none reported their skill levels decreased relative to their initial levels and 87.4% (=39.1% + 23.3% + 12.0%) reported their skill levels have improved compared to their levels at the time of hire.

Covariates we used include: whether or not worker has a job-related license('License'); sex; age; education level; dummy variable for receiving formal trainings('Formal')[6]; job satisfaction('satisfaction1' $\sim$ 'satisfaction5')[7]; job complexity('complexity1' $\sim$ 'complexity4')[8].

[5]Translated by the authors.

[6]It would be better to have a quantitative measure for formal training for the entire periods that one worked for the company the but the survey only provided the amount of formal training at year 2011. So we treated it as an indicator variable which is 1 if a worker received the formal training in 2011 and 0 for otherwise. A careful examination of the data revealed that the average tenure for workers who received a formal training in 2011 was 9.9 years, while workers who did not receive formal training in 2011 have an average 13.3-year tenure.

[7]Subjective level of job satisfaction level was reported in a five point Likert scale.

[8]The question regarding job complexity was "what is the nature of your job?" Surveyees chose one of the following answers: (1) tedious and routine; (2) there are occasional new events; (3) new events occur often; (4) every job is new and challenging. Since informal training is experienced

Table 2: Descriptive statistics for other covariates

Variable		Mean	Std. Dev.	Min	Max
License	1 if one has a license related to current job	0.075	0.264	0	1
Sex	1 if male	0.812	0.39	0	1
Age		28.5	7.3	15	61
edu_{mi}	$\leq$ middle school	0.069	0.253	0	1
edu_{hi}	highschool graduate	0.241	0.427	0	1
edu_{voc-hi}	vocational highschool graduate	0.311	0.462	0	1
edu_{col}	college graduate	0.177	0.382	0	1
edu_{univ}	$\geq$ university graduate	0.202	0.401	0	1
Formal	1 if one receives formal training in 2011	0.315	0.865	0	1
peer1	1 if one learns nothing from peer interactions	0.099	0.299	0	1
peer2	1 if one learns seldom from peer interactions	0.257	0.438	0	1
peer3	1 if one learns quite a lot from peer interactions	0.482	0.5	0	1
peer4	1 if one learns very much from peer interactions	0.162	0.368	0	1
self1	1 if one learns nothing from doing by oneself	0.041	0.199	0	1
self2	1 if one learns seldom from doing by oneself	0.237	0.425	0	1
self3	1 if one learns quite a lot from doing by oneself	0.542	0.498	0	1
self4	1 if one learns very much from doing by oneself	0.180	0.384	0	1
satisfaction1	1 if job is very unsatisfactory	0.005	0.073	0	1
satisfaction2	1 if unsatisfactory	0.051	0.219	0	1
satisfaction3	1 if neutral	0.487	0.500	0	1
satisfaction4	1 if satisfactory	0.401	0.490	0	1
satisfaction5	1 if very satisfactory	0.056	0.229	0	1
complexity1	1 if one's job task is tedious and routine	0.528	0.49	0	1
complexity2	1 if there are occasional new events	0.316	0.465	0	1
complexity3	1 if new events occur often	0.131	0.337	0	1
complexity4	1 if every job is new and challenging	0.025	0.158	0	1
Tenure		12.2	8.6	1	41

There were two variables related to informal training: how much one learned from peers (peer-learning, 'peer1' $\sim$ 'peer4'); how much one learned by doing his/her job (learning-by-doing, 'self1' $\sim$ 'self4'). Both were at a four point Likert scale, one being 'little' to four being 'a lot'. Table 2 presents some descriptive statistics of them.

in the context of working and it is highly firm-specific, it is reasonable to assume that certain properties of working environments would affect the effectiveness of training. The tone of Korean of the question was neutral in the sense that surveyees might have interpreted, for example (1) tedious and routine as 'simple and easy' or 'boring' or for another example (4) every job is new and challenging as 'hard and tough' or 'exciting'.

Other than these variables, we included the following five point Likart scale variables to control for corporate culture and organizational features (‘culture-related variables’ henceforth) : ‘trust level between executive managers and employees(*trust*)’, ‘communication between executive managers and employees(*inform*)’; ‘performance oriented culture(*perform*)’; ‘teamwork-based job culture(*team*)’; ‘how competitive the corporate is(*competition*)’. Although these culture-related variables were categorical as some other variables were, we included them as they were reported as if they were interval variables simply because we used them only for controlling purpose.

A main contribution of our paper in terms of econometrics is that we developed a bivariate probit model which utilized dynamic aspect of cross sectional data. Since our productivity variables y_0 and y_1 were ordered and categorical, we chose to use an ordered bivariate probit model. But we wanted to add a feature that allowed for y_1 to depend on y_0. Let y_t^*, $t=0,1$, be true but latent skill levels from which reported y_t were generated. The relationship between y_t^* and y_t are

$$y_t = \begin{cases} 1 \text{ if } y_t^* \le \alpha_1, \\ 2 \text{ if } \alpha_1 < y_t^* \le \alpha_2, \quad \text{for } t=0,1. \\ 3 \text{ if } \alpha_2 < y_t^*, \end{cases}$$

Let $\alpha_0 = -\infty$ and $\alpha_3 = \infty$ for notational convenience.

The true initial skill level y_{0i}^* is assumed to be determined by some covariates x_i as follows:

$$y_{0i}^* = x_i'\beta + v_{0i}. \tag{1}$$

After i got hired his/her initial skill deteriorates or becomes obsolete at a rate of δ each period as time goes by but her overall skill is enhanced by some covariates z_i which include informal training. Her skill level by the time of survey becomes

$$y_{1i}^* = (1-\delta)^{T_i} y_{0i}^* + z_i'\gamma + v_{1i}. \tag{2}$$

To better understand the background of equation (2), consider the following dynamics. Assuming that the initial productivity level at the entry can be represented as y_0^*, productivity level at the time period $t=1$ can be written as follows: $y_{t=1}^* = (1-\delta)y_0^* + z_{t=1}'\gamma + u_{t=1}$. Here, covariate vector $z_{t=1}$ characterizes factors affecting the change in productivity level from period 0 to period $t=1$. Similarly we can model the second-year productivity level as follows: $y_{t=2}^* = (1-\delta)y_{t=1}^* + z_{t=2}'\gamma + u_{t=2}$. Repeating this step T_i-times, we get following equation:

$$y_{T_i}^* = (1-\delta)^{T_i} y_0^* + \sum_{t=1}^{T_i}(1-\delta)^{T_i-t} z_t'\gamma + \sum_{t=1}^{T_i}(1-\delta)^{T_i-t} u_t. \tag{3}$$

Comparing equation (2) with equation (3), z_i in equation (2) is understood to correspond to $\sum_{t=1}^{T_i}(1-\delta)^{T_i-t}z_{i,t}$. Therefore z_i in our model (2) may be interpreted as cumulative effects of past z's.[9]

Let $\{(y_{0i}, y_{1i}, x_i', z_i', T_i)\}_{i=1}^n$ be our data and $\theta \equiv (\alpha_2, \delta, \beta', \gamma')'$ be the parameters to estimate. As a normalization constraint, we set $\alpha_1 = 0$. To estimate the parameters, we assumed conditional bivariate normality of (v_0, v_1). More precisely,

$$\begin{bmatrix} v_{0i} \\ v_{1i} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}\right) \text{ given } (x_i, z_i). \tag{4}$$

Re-Arranging (2) and combining it with (1), we have

$$\begin{bmatrix} 1 & 0 \\ -(1-\delta)^{T_i} & 1 \end{bmatrix} \begin{bmatrix} y_{0i}^* \\ y_{1i}^* \end{bmatrix} = \begin{bmatrix} x_i'\beta \\ z_i'\gamma \end{bmatrix} + \begin{bmatrix} v_{0i} \\ v_{1i} \end{bmatrix}$$

or

$$\begin{bmatrix} y_{0i}^* \\ y_{1i}^* \end{bmatrix} = \begin{bmatrix} x_i'\beta \\ (1-\delta)^{T_i} x_i'\beta + z_i'\gamma \end{bmatrix} + \begin{bmatrix} \varepsilon_{0i} \\ \varepsilon_{1i} \end{bmatrix},$$

where

$$\begin{bmatrix} \varepsilon_{0i} \\ \varepsilon_{1i} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ (1-\delta)^{T_i} & 1 \end{bmatrix} \begin{bmatrix} v_{0i} \\ v_{1i} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & (1-\delta)^{T_i} \\ (1-\delta)^{T_i} & 1+(1-\delta)^{2T_i} \end{bmatrix}\right)$$

conditional on (x_i, z_i). Therefore, the conditional joint pdf of $(\varepsilon_{0i}, \varepsilon_{1i})$ given (x_i, z_i, T_i) is

$$\begin{aligned} & f_\varepsilon(\varepsilon_{0i}, \varepsilon_{1i} | x_i, z_i, T_i; \delta) \\ &= \frac{1}{2\pi} \exp\left\{-\frac{1}{2}\left(\left(1+(1-\delta)^{2T_i}\right)\varepsilon_{0i}^2 - 2(1-\delta)^{T_i}\varepsilon_{0i}\varepsilon_{1i} + \varepsilon_{1i}^2\right)\right\}. \end{aligned} \tag{5}$$

Given the $f_\varepsilon(\varepsilon_0, \varepsilon_1 | x_i, z_i, T_i; \delta)$, we can derive the following probabilities.[10]

$$\begin{aligned} p_{jk,i}(\theta) &\equiv \Pr[y_{0i} = j, y_{1i} = k] = \Pr[\alpha_{j-1} < y_{0i}^* \leq \alpha_j, \quad \alpha_{k-1} < y_{1i}^* \leq \alpha_k] \\ &= \Pr[\alpha_{j-1} - x_i'\beta < \varepsilon_{0i} \leq \alpha_j - x_i'\beta, \\ &\qquad \alpha_{k-1} - (1-\delta)^{T_i}x_i'\beta - z_i'\gamma < \varepsilon_{1i} \leq \alpha_k - (1-\delta)^{T_i}x_i'\beta - z_i'\gamma] \\ &= \int_{\alpha_{j-1}-x_i'\beta}^{\alpha_j - x_i'\beta} \int_{\alpha_{k-1}-(1-\delta)^{T_i}x_i'\beta - z_i'\gamma}^{\alpha_k - (1-\delta)^{T_i}x_i'\beta - z_i'\gamma} f_\varepsilon(\varepsilon_0, \varepsilon_1 | x_i, z_i, T_i; \delta) d\varepsilon_0 d\varepsilon_1. \end{aligned} \tag{6}$$

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[9]Had we had individual worker level panel data available, we would have modeled with a dynamic panel data model. As described earlier, however, the HCCP is cross sectional at worker level. So, we attempted to "mimic" a dynamic panel data model using available cross-sectional data by setting up model (2).

[10]For notational simplicity, we will assume the conditioning of x_i, z_i, T_i only implicitly.

The log likelihood function is, therefore, $\mathscr{L}_n(\theta) = \sum_i \sum_j \sum_k 1_{\{y_{0i}=j, y_{1i}=k\}} \ln p_{jk,i}(\theta)$.[11]

We did the simulated quasi ML estimation (SQMLE) since exact evaluation of choice probabilities would involve highly burdensome procedure of solving the double integral. Details of our estimation procedure are provided in the Appendix.

For covariate vector x, we used 'License', 'Sex', 'Age', and 'edu_{hi}' to 'edu_{univ}'. For covariate vector z, we used 'Formal' and two kinds of informal training variables 'peer2' to 'peer4' and 'self2' to 'self4' as well as culture-related variables.

3. ESTIMATION RESULT

Table 3 presents the estimation result of the model. Before reading the results, we need to keep in mind that the interpretation of coefficients is not straightforward. Unlike linear regression models where coefficient estimates coincide with related partial effects, parameter estimate of our model may not be directly interpreted as partial effects.

Coefficient for formal training('Formal') is about 0.9 and highly significant, implying formal training has significant and positive impacts on skill accumulation. When it comes to informal training, only 'peer4' and 'self4' are significant at 10% level. Interestingly, coefficients of 'peer's become greater as peer-learning level increases(that is 'peer2' $<$ 'peer3' $<$ 'peer4'). This result suggests that workers who learned from peers more experienced higher skill level increase by informal training. Another mode of informal training - namely leaning-by-doing - shows a similar pattern. Coefficients of 'self's are 'self2' $<$ 'self3' $<$ 'self4', too. This also is suggestive of higher skill level increase by informal training of workers who learned from doing their jobs.

Between two modes of informal training, peer-learning and learning-by-doing, coefficients of the latter are greater. We may interpret this result as the latter is more important in skill increase.[12]

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[11]Unlike usual ordered probit models where a constant term in β is not estimable, we were able to estimate it. To explain this feature, let us assume $x_i'\beta = \beta_0 + \beta_1 x_i$ for simplicity. Then formula (6) becomes

$$\int_{(\alpha_{j-1}-\beta_0)-\beta_1 x_i}^{(\alpha_j-\beta_0)-\beta_1 x_i} \int_{(\alpha_{k-1}-(1-\delta)^{T_i}\beta_0)-(1-\delta)^{T_i}\beta_1 x_i - z_i'\gamma}^{(\alpha_k-(1-\delta)^{T_i}\beta_0)-\beta_1 x_i - z_i'\gamma} f_\varepsilon(\varepsilon_0, \varepsilon_1 | x_i, z_i, T_i; \delta) d\varepsilon_0 d\varepsilon_1.$$

Therefore, β_0 is identified due to $(1-\delta)^{T_i}$.

[12]This result is qualitatively similar to Destré et al. (2008).

Table 3: Estimation Result

	variable	**estimate**	**t-value**	**p-value**
***	License	0.5951	6.9495	0
***	Sex	0.7863	10.2668	0
	Age	0.1086	0.4788	0.632
*	age2	0.0616	1.7812	0.0750
	edu_{hi}	-0.1776	-1.633	0.102
	$\text{edu}_{\text{voc-hi}}$	-0.0494	-0.4561	0.648
	edu_{col}	0.0244	0.2175	0.828
	edu_{univ}	0.1512	1.3433	0.179
***	Formal	0.1918	3.7843	0.0
	peer2	-0.0331	-0.3404	0.734
	peer3	0.1068	1.1145	0.265
*	peer4	0.1895	1.6872	0.092
	self2	0.1599	1.1707	0.242
	self3	0.2156	1.5754	0.115
*	self4	0.2428	1.6638	0.096
**	satisfaction2	0.4520	2.4995	0.012
***	satisfaction3	0.5137	3.050	0.002
***	satisfaction4	0.7007	3.8541	0.0
***	satisfaction5	1.0304	4.6249	0.0
*	complexity2	0.1031	1.90	0.057
***	complexity3	0.6047	7.6403	0.0
***	complexity4	0.6183	3.5480	0.0
	trust	0.0556	1.5869	0.113
	inform	0.0530	1.6014	0.109
	perform	0.0167	0.4692	0.639
	team	0.0269	0.7359	0.462
	competition	0.0149	0.4481	0.654
***	Intercept	-2.0315	-5.5997	0.0

Significant at: *** 1%; ** 5%; * 10%.

The greatest magnitude of significant estimates on informal training is 0.24, while the estimate on formal training is 0.19. Although these two estimates are not directly comparable because of their different units of measure, this result at least suggests that ignoring the effect of informal training can severely exaggerate the effect of formal training on productivity level.

Table 4: Rate of Skill Deterioration

	variable	beta	t-value	p-value
***	δ	0.943	191.692	0
***	α_2	1.654	49.526	0

Significant at: *** 1%; ** 5%; * 10%.

Table 4 shows that the estimate of the depreciation rate is 0.94.

Since data on tenure was divided by 10, the depreciation level in one year is about 0.24(from $(1-0.94) = (1-x)^{10}$), which means that after one year, about 24 percent of original skill level wears off. A half life of skill level, therefore, is estimated to be about 2.4 years (from $(1-0.24)^{2.4} \approx 0.5$). The depreciation rate seems very high however it may be indicative of subjective feeling of being obsolete in a fast changing job environment (consider IT and factory automation for example) in addition to actual skill depreciation.

Deterioration of the skill may natually occur possibly because of two reasons: first, as new technologies develop, already obtained skill and knowledge loses competitiveness; second, workers may lose proficiency if there is no training even if no new technologies develop. Both cases indicate the importance of formal and informal trainings not only for workers to adapt new technologies, but also to maintain their skill levels up-to-date.

Before moving for further discussions, we want to mention a thing about $\hat{\delta}$ that there may be another reason that we have such a large estimate. Table 1 shows that there were no workers whose skill levels dropped. The data make sense because a worker who didn't keep his/her skill level up-to-date would have been fired already i.e. 'only the fittest survived', to say it simple. This intuition suggests that the data may have been truncated to 'the fittest' and may suffer from sample selection problem. Data truncation may be able to explain such a high $\hat{\delta}$. If indeed only the fittest survived, those who are in the sample will have updated their skill level more rapidly and frequently, which will have led observed depreciation rates to a greater level than average depreciation rates. For now, we won't put any of our speculations about such a high depreciation rate estimate forward.

Our model didn't take this potential sample selection into account and allowed for y_1 to be lower than y_0. We may have different results if we model

(4) differently, say, as a truncated bivariate normal. Unfortunately to us, various truncated bivariate ordered probit models that we tried didn't work well. Theory and Monte Carlo simulations for such models showed they don't estimate parameters consistently. One of our future researches is to develop an ordered outcome econometric model that takes data truncation into account.

Partial effect is either $\frac{\partial}{\partial w}\Pr[y_0 = j, y_1 = k|x,z]$ with w being one of (x,z) in case of continuous variables or $\Pr[y_0 = j, y_1 = k|x,z] - \Pr[y_0 = j, y_1 = k|x',z]$ (or similarly $\Pr[y_0 = j, y_1 = k|x,z] - \Pr[y_0 = j, y_1 = k|x,z']$) in case of discrete variables. Partial effects may be calculated based on senarios in mind. For example, one may want to compute partial effect of a variable when all other variables are held at their sample medians. Or, one may want to calculate partial effect of a variable while all other variables are held as they are in the sample, namely *status quo*. Let w, the variable of our interest, be one of z and z_- all other variables in z. Then the average effect of changes in w from w^0 to w^1 while all other variables stay at the *status quo* on probabilities of $(y_0 = j, y_1 = k)$ is $E[\Pr[y_0 = j, y_1 = k|x, w^1, z_-]] - E[\Pr[y_0 = j, y_1 = k|x, w^0, z_-]]$, where the expectation is with respect to (x, z_-), which may be called 'average effect of changes in w on the probability of $(y_0 = j, y_1 = k)$'. The average effect is estimable by

$$\frac{1}{n}\sum\nolimits_{i=1}^{n}\left(\Pr[y_0 = j, \widehat{y_1 = k}|x_i, w^1, z_{-,i}] - \Pr[y_0 = j, \widehat{y_1 = k}|x_i, w^0, z_{-,i}]\right), \quad (7)$$

where

$$\begin{aligned}&\Pr[y_0 = j, \widehat{y_1 = k}|x_i, w, z_{-,i}] \\ &= \int_{\alpha_{j-1}-x_i'\hat{\beta}}^{\hat{\alpha}_j - x_i'\hat{\beta}} \int_{\hat{\alpha}_{k-1}-(1-\hat{\delta})^{T_i}x_i'\hat{\beta}-(w,z_{-,i})'\hat{\gamma}}^{\hat{\alpha}_k-(1-\hat{\delta})^{T_i}x_i'\hat{\beta}-(w,z_{-,i})'\hat{\gamma}} f_\varepsilon(\varepsilon_0, \varepsilon_1|x_i, w, z_{-,i}, T_i; \hat{\delta})\, d\varepsilon_0 d\varepsilon_1.\end{aligned}$$

Monte Carlo numerical integration may be used.

Average effect of some some selective variables on probabilities of $(y_0 = j, y_1 = k)$ are presented in Table 5. Column title p_{jk} stands for changes in probability of $(y_0 = j, y_1 = k)$. Since all variables of interest are discrete, changes in consideration was from 0 to 1. Cells with positive values are shaded green.

Since partial effects of average partial effects will differ senario to senario, we don't want to emphasize the results in Table 5. One may find it interesting that the average effects of 'Formal' are similar to that of 'self3' and greater than that of 'self4' while coefficients of 'Formal' is estimated smaller than that of both 'self3' and 'self4'. The result may change if we adopt other senarios, however.

Table 5: Estimates of Average Effects

variable	p_{11}	p_{12}	p_{13}	p_{22}	p_{23}	p_{33}
Formal	-0.0487	-0.0698	0.1185	-0.0433	0.0555	0.0049
peer4	-0.0109	-0.0232	0.0341	-0.0129	0.0152	0.0012
self4	-0.0135	-0.0254	0.0389	-0.014	0.0173	0.0014
satisfaction2	-0.0065	-0.003	0.0095	-0.0028	0.0047	0.0005
satisfaction3	-0.0546	-0.0429	0.0974	-0.0324	0.0467	0.0042
satisfaction4	-0.0294	-0.0592	0.0886	-0.0319	0.0394	0.0032
satisfaction5	-0.002	-0.0095	0.0115	-0.0042	0.0046	0.0003
complexity2	-0.0282	-0.0378	0.066	-0.0247	0.0323	0.0029
complexity3	-0.006	-0.0193	0.0254	-0.0113	0.0125	0.001
complexity4	-0.0014	-0.0028	0.0042	-0.0021	0.0023	0.0002

4. CONCLUSION

We developed a bivariate ordered probit model that has a dynamics-like aspect in skill level depreciation and utilized nice features of 'Human Capital Corporate Panel' in order to understand effects of informal training on productivity. Our finding is that skill level depreciates about 24% every year on average, which is quite high. A half life of skill is about 2.4 years according to this result, which is pretty short. It may be indicative of fast changing job environment in Korea or due to data truncation problem.

We also found significant effects of both formal and informal training on skill level increase. The effect of formal training on skill accumulation was positive and highly significant. Both modes of informal training, peer-learning and learning-by-doing, positively affected although the coefficients were statically less significant than the coefficient of formal training. Coefficients of 'peer's and 'self's showed one who learned more from either peers or doing his/her own jobs had experienced greater skill level improvement.

APPENDIX: IMPLEMENTATION OF SIMULATED QUISI-MAXIMUM LIKELIHOOD ESTIMATION(QMLE)

Let $A = x'\beta$ and $B = (1-\delta)^T x'\beta + z'\gamma$. Then,

$$\begin{aligned} y_0^* &= x'\beta + v_0 \equiv A + v_0, \\ y_1^* &= (1-\delta)^T y_0^* + z'\gamma + v_1 = (1-\delta)^T x'\beta + z'\gamma + (1-\delta)^T v_0 + v_1 \\ &= B + (1-\delta)^T v_0 + v_1. \end{aligned}$$

The probability of choosing $y_0 = 1$ and $y_1 = 1$ can be written as follows:

$$\begin{aligned} P_{11} &\equiv Pr[y_0 = 1, y_1 = 1] = Pr[y_0^* \le 0, y_1^* \le 0] \\ &= Pr[v_0 \le -A, v_1 \le -B - (1-\delta)^T v_0] \\ &= Pr[v_0 \le -A] Pr[v_1 \le -B - (1-\delta)^T v_0 | v_0 \le -A] \\ &= \Phi(-A) \int_{-\infty}^{-A} \Phi(-B - (1-\delta)^T s)\phi(s) ds. \end{aligned}$$

Simulated QML estimation can be done by using simulated probabilities instead of their exact counterparts. Simulation of P_{11}, for instance, can be done using Monte Carlo integration:

(Step 1) Draw H-many random numbers from standard normal distribution:$\{s^{(h)}\}_{h=1}^{H}$

(Step 2) Calculate $\hat{P}_{11} \equiv \Phi(-A) \cdot \frac{1}{H} \sum_{h=1}^{H} \Phi(-B - (1-\delta)^T s^{(h)})$

with a very large H. This $\hat{P}_{11}$ gives a simulated probability of P_{11}. Note that since A and B are dependent on individual i, we have different $P_{11,i}$ for different i.

Other probabilities can be simulated in a similar way. Using these, we can calculate our SQMLE object function:

$$\mathcal{L}_n(\theta) = \sum_{i=1}^{n} \sum_{j=1}^{3} \sum_{k=1}^{3} 1_{\{y_{0i}=j, y_{1i}=k\}} \ln \hat{P}_{jk,i}(\theta).$$

Estimation of variances for $\hat{\theta}$ is identical to QMLE.

REFERENCES

Altonji, Joseph G. and James R. Spletzer (1991). “Worker characteristics, job characteristics, and the receipt of on-the-job training”. In: *Industrial and Labor Relations Review* 45.1, pp. 58–79.

Destré, Guillaume, Louis Lévy-Garboua, and Michel Sollogoub (2008). “Learning from experience or learning from others? Inferring informal training from a human capital earnings function with matched employer-employee data”. In: *Journal of Socio-Economics* 37.3, pp. 919–938.

Eraut, Michael (2004). “Informal learning in the workplace”. In: *Studies in Continuing Education* 26.2, pp. 247–273.

Frazis, Harley and Mark A. Loewenstein (2005). “Reexamining the returns to training: Functional form, magnitude, and interpretation”. In: *Journal of Human Resources* 40.2, pp. 453–476.

Kunze, Astrid (2002). “The Timing of Careers and Human Capital Depreciation”. In: *Discussion Paper Series, IZA DP No. 509*. Institute for the Study of Labor (IZA).

Liu, Xiangmin and Rosemary Batt (2007). “The Economic Pay-Offs to Informal Training: Evidence from Routine Service Work”. In: *Industrial and Labor Relations Review* 61.1, pp. 75–89.

Marsick, Victoria J. and Karen E. Watkins (1990). *Informal and Incidental Learning in the Workplace*. New York: Routledge.

McFadden, Daniel (2008). “Human Capital Accumulation and Depreciation”. In: *Applied Economic Perspectives and Policy* 30.3, pp. 379–385.

Watkins, Karen E. and Victoria J. Marsick (1992). “Towards a theory of informal and incidental learning in organizations”. In: *International Journal of Lifelong Education* 11.4, pp. 287–300.

Weiss, Andrew (1994). “Productivity Changes without Formal Training. In Training and the Private Sector”. In: *Training and the Private Sector(Ch.5)*. Ed. by Lisa M. Lynch. National Bureau of Economic Research, Inc.