Reappraising the Job-Training Effect on Labor Market Outputs of Korean Women

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Abstract

Investigating on the effect of job training has spread out it's interest in studying female labor outcomes. Since female labor is likely associated with child care and other house works, the characteristics of female labor is quite different from one of male. It implies the role as well as the effect of job training of female might be unlike in case of male. It requires different methodologies that enable to handle this subject. In this paper I estimated job training effect of Korean female, using applied fixed effect model with 8 years of panel data. With various specifications of wage equations including self-selection correction terms, I have found positive effect of female job training. From final econometric specification, I have got estimated coefficient of job training 0.049. It implies if one female got 1% point of days of job training, her wage would be increased up to 4.9 %.

I. Introduction

In studying on experience-earning profile or understanding of structure of labor market, human capital accumulation has become a key word in labor economics. Since the education system has been equalized for most of people, role of experience after formal schooling in horizon of lifetime has taken more attentions. According to human capital accumulation theory, after the formal schooling, people can achieve the human capital through working experience. This working experience can be defined two components, general knowledge through mature process, aging, and

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specific job training. Among these two different working experiences, job training has kept our attentions because job training might provide various and strong effects directly and indirectly on wage itself. It is not only important for employee, but also employers have paid attention of job training, because job training could reduce the cost of turnover.

Several decades back, Investigating on effect of job training has spread out it's interest in studying female labor outcomes. Since female labor is likely associated with child care and other house works, the characteristics of female labor is quite different from male. It implies the role and effect of job training might be unlike in case of male. Different role and different functioning with complicity female labor itself require different methodologies that enable to handle this subject. Nowadays it became one of the most challenging topics in economics.

In this paper, I investigate the effect of job training for Korean female on wage. With using rich data set from Korean labor institute, I could evaluate the effect of job training of Korean female during 1999-2004 with several econometric specifications. Before start the empirical estimation, I would like to scrutinize the theoretical considerations of job training and job training of female labor with conventional as well as alternative point of views and also take a look at empirical results from previous literatures. This would be in the first part of this paper. After that I propose the several methodologies that I will use for empirical analysis in this paper. The third part, I will show the main results from different models. Lastly, I will conclude and discuss about them.

II. Job Trainings for Female labors : Theoretical & Empirical Considerations

Labor force attachment of female has been increased along the increasing attendance of female in formal education system. However, many current the labor market outputs, earnings and occupational choices, still show the significant difference between male and female. Many studies of the earnings of female claim that the key feature of this difference is associated with house-works, for instance child care and care of other family members in results in smaller investment of human capital along the horizon of female's life.

As I mention before, post human capital accumulation can be accomplished via job training and via maturation process (aging). However, job training plays more important role in labor market, because it is directly related with specific skills in labor market favor. Especially for female, job trainings, general form as well as firm specific form, could be crucial. In other words, often time they have to decide quite regardless their willingness and reenter the labor market. This discontinuity of working experience influences their working profiles and it ends up with poor occupational opportunities. Job training would help them to catch up their lost labor experience.

In this sense, Sen's capability approaches shed light on job training especially for female. Although his argument is focusing on female's economic activity in general[2], it is not difficult to extend his theory to emphasize the role of job training for female. In other words, job training could support lack of opportunity of economic activities for female. This is important not only the raising their earnings but also it makes them recognize their identification and develop their empowerment per se through the economic role in outside of family.

Job training of female has been noticed crucial functioning of the labor market, however, it is likely dominated by the role labor market. Intuitively, Employer's prior expectations of female labor or female labor's lower expectation of their own lifetime labor force attachment associated with their commitment of child care affect not only the opportunity of job training but also their choices of period & types of job training[3]. Obviously it leads female labor to lower quality of job as well as lower experience and earning profiles compared to one that male takes.

According to theory of human capital accumulation, implication of effect of job training would be straight forward. And this hypothesis of human capital accumulation for job-training has been tested, making the theoretical relationship between investment of job training and experience-earnings profiles. Ashenfelter's paper (1978) is known as the first empirical study for job-training in U.S., and he found the positive wage effect on participants in CETA (the comprehensive Employment and Training Act). Lynch(1992), Levine (1993), Lowewnstein & Spletzer (1997) & (1998) and so forth, have tried directly to measure the effect of job-training with supported by a rich data set such as Panel Study of Income Dynamics (PSID), National longitudinal Survey of Youth (NLSY), and Current Population Survey (CPS). For measuring the effect of job-training, the most important issue is how to measure "True Effect": the difference between two outcomes, one is from participant on job-training and the other one is from participant if they are not participate the job-training (potential participants). But as we expect, we cannot observe same person who participate the job-training at the same time does not. This impossibility of observable counterfactual is potential problem of measuring of true effect.

Practically, counterfactual is estimated by using treatment groups and comparison groups

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[2]H claimed in his various papers thatthe relative respect andregar for womes well-being is strongly influenced by such variables as womes ability to earn an independent income, to find employment outside the home, to have ownership rights and to have literacy and be educated participants in decisions with and outside the familSen, A. (1999), Development as Freedom, p 19. That is, womesvoice and agenc would be realized throughthei independence and empowerment such as womes earning power, economic role outside the family, literacy and education, property right and so forth. And, of course, this argument is going well beyond womes empowerment itself, it can affect on those of children as well as influence the nature of thepubli discussion on a variety of social subjects, poverty, environmental priorities, human right in general

[3]Barron, John M., Dan Black, and Mark A Loewenstein, 1989, " Job Matching and On the job training."*Journal of labor Economic* 8 (1, 1:19

and in this case, we assume that "treat" should be distributed randomly. That is, treatment groups and comparison groups divided by randomly therefore the expectations of various characteristics, observable and unobservable, are same in both of groups by principle of probability, so that there is no selection bias taking place. In other words, if we use experimental data, we could derive true effect. But since most of evaluating analysis of job-training (including public program) are not using experimental data, potential sample bias problem due to non random selection of graining participants influenced seriously on measurement of true effect of job-training. Various econometric literatures have been pointing out this problem (i.e. Heckman and Robb (1985), Ashenfelter and Card (1985), and Lalonde (1986) etc). They had claim that "the results of evaluation of effect are highly sensitive to the different stochastic assumptions made about the selection process"[4].

Recently many other econometric literatures have been focusing on this problem, and made great effort to suggest relevant solutions. One of methodologies that prevailed over the researchers in these days is Propensity Score Matching (PSM). Intuitively the Matching is Selecting subjects similar in X across the Treatment and Control groups. In doing so, it could be done to control for unobserved problem. However, there is some problem in doing so. If X vector is high–dimensional, then it is difficult to find matching subjects. In 1983, Rosenbaum and Rubin (1983) suggest solution for this problem, called "Propensity Score Matching": Functions of the relevant observed covariates X such that the conditional distributions of X given P(X) is independent of the assignment into treatment, and the one possible way of this process is propensity score, the probability of participating in a program given observed characteristics X. so that measuring the effect from weighting of Propensity score matching could provide reasonable result without selection bias. Dehejia, R.H. and Wahba, S. (1999) revaluated the Lalonde (1986) data by using nonparametric techniques, Propensity Score Matching, so that they came to far more positive conclusions about the potential quality of observation data than did Lalonde. Lechner Michael (1999) also used same approach with German data. Although many people appraised Propensity Score matching method would be best way to deal with selection problem, it still depends on observable variable so that couldn't solve the problem completely.

Practically, as I mention, measuring of true effect of job training of "*female"* on labor market outcomes is more complicated. Because in many empirical applications, not only female labor market participants are not randomly drawn, but also because observations of female participants are limited in available data set, it is hard to clarify the selection process itself, therefore it is extremely hard to identify the effect of job training on their actual wages. In other words, because the situation of "*female*" in labor market and job training that prone to be in favor of male labors, the selection

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[4]Lechner, Michael (1999), Earnings and Employment Effects of Continuous Off-the-Job Training in East Germany After Unification. p74

process of job training of female even more complicated through the real data. Technically speaking, we have to deal with dual selection problems and these are entangled with unobserved factors.

Even though investing of effect of job training has long trace in many developed country theoretically and empirically, study of Job training in Korea had been negligible. Many studies of job training have been developed in Korea just aftermath of Financial Crisis in 1997. For instance, Kang and Lee (1999), Kang, Lee, and Kim (2000), and Kang and Roh (2001) analyzed the effect of job-training on economic wage and unemployment with using simple treatment effect approach[5]. But they did not control individual characteristics which are likely correlated with training itself. Therefore it is hard to say that their models were enough to obtain relevant results. Kim (2002) has criticized the limitation of previous model with using cross session data. He pointed out that the reason why the effect on wage was not significant was because of lack of control of individual characteristics. He utilized two years panel data with controlling the individual characteristics. In his model, however, he didn't include year dummy[6] and also he did use years of schooling instead of using schooling dummy. Consequently his model also was not accurate enough to get adequate results. Recently Lee, M.J. and Lee, S.J. use different data, combining two sub-data files[7], and applied Weibull MLE for estimating unemployment duration. They, however, applied semiparametric model, because it still stood on cross session data set, it would not be free from above problems. Lee, S.W. (2003) is one of the paper that applied PSM method with KLIPS(1998-2000, 3 years), and showed the positive result of effect on wage. Lee, M.J & Tae (2003) have coped with dynamic process of job training of female more seriously. They pointed out once a women makes the choice of working (versus non-working), the simple fact that her works now will increase the likelihood that she works in future, with the other things held constant[8]. That is, present working lead likely to another work in next period. Their work is not precisely deal with female's experience-earning profile, however it has shed light on headstone of function of job training especially for female in Korea.

In sum, theoretically accumulating human capital through the job training might be more crucial than through the formal education in labor market. It is job training for female that could play vital role in their attachment in labor market as well as their earning. Furthermore, the effect would be beyond their possible labor activity, we would expect that it would be one the way to develop female

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[5]Even if all of them used KLIPS, but since they didt have enough data as a panel, their analysis were as same as cross session data analysis

[6]Year dummy is important, especially Korean data, because the data extracted just after Financial crisis, it would affect seriously in many labor market outcomes. It would be crucial factor for taking into account the effect of job-training in Korea.

[7]One is from the Center for Employment Information in the Department of Labor in South Korea, the other one is the unemployment-insurance file.

[8]Lee & Tae, (2003), Dynamic Labor-Participation Behavior of Korean Women. P 2. This effect is calledstate dependenc orhooked on effec. This effect much more well known in advertising effect on sale.

as a human being since the function of job training works through the complicated and unbalanced female labor market and society. Ironically, because the perplexed states of female, it is hard to evaluate true effect of job training for female. Practically there is main subject in this matter. Selection process of job training itself and selection process of decision of work. In this paper, I try to manage these two problems through panel data. Following section, I describe the detail econometrical methodology for that.

III. Empirical Methodology & Estimates

III-1. Methodology: Dif-n-Dif & Fixed Effect Model

There are several applications for measuring the true effect of job training. In this paper, key econometric strategy is standing on utilizing of the difference in difference (Dif-n-Dif) methodology. The basic concept of this methodology is following.

(1) $\hat{\delta}_{DD} = (\overline{Y}^T_{yr1} - \overline{Y}^T_{yr2}) - (\overline{Y}^C_{yr1} - \overline{Y}^C_{yr2})$

, where $\overline{Y}^T_{yr1}$: Average of outcome from treat group at time 1 (before),

$\overline{Y}^T_{yr2}$: Average of outcome from after treat group at time 2 (after),

$\overline{Y}^C_{yr1}$: Average of outcome from controlled group at time 1 (before),

$\overline{Y}^C_{yr2}$: Average of outcome from controlled group at time 2 (after).

As we know, if we use the cross section data in order to estimate the unbiased coefficient of job training, there are possible problems that there might be systematic, unmeasured in difference in treated group and controlled groups that have nothing to do with job training. On the other hand, if we ignore the two different groups and only consider the changing wage on treated group, it might be just measure of something that related with over time but unrelated with job training itself. Intuitively, Dif-n-Dif methodology compare the time changes in the means for the treated group and controlled groups in a way that both group specific and time specific effects are allowed for. Therefore $\hat{\delta}_{DD}$ is unbiased estimate of job training unless the job training is not systematically involved with other covariates that affect on wage or error term in wage equation.

Since I utilize the panel data, I would use the fixed effect model with using entire years of panel data. However, because there is not enough observation of job trainee in female population, I adapt Dif-n-Dif with taking advantage of panel data. In other words, I will take only two year as a outcome variable from before and after the job training period, and with using panel data, I control the individual characteristics. The operational model is following;

(2) $$Y_{i98,05} = \alpha_i + \beta_x X_{i98,05} + \beta_d D_{i98,05} \cdot Yr05 + \beta_{yr} Yr05 + \varepsilon_{i98,05}$$

,where, D_i = 1 if female in job-training during any year between1999 & 2004, otherwise =0

Through this model, we can get ride of unobserved individual characteristics therefore we could get an unbiased estimate of β_d . In this case, we might need to reconsider a dummy variable of job training, D_i. In other words, a dummy variable, D_i can not capture the intensity of job training. Hence, I use the number of days (JT_Days) that one has taken for job training during 1999 & 2004 rather than use the simple dummy variable of job training. Therefore I rewrite the wage equation (2) with changing main interest variable,

(3) $$Y_{i98,05} = \alpha_i + \beta_x X_{i98,05} + \beta_d JT\_Days_{i98,05} \cdot Yr05 + \beta_{yr} Yr05 + \varepsilon_{i98,05}$$

,where *JT_Days* : Numbers of days for job training in any year between 1999 & 2004.

In this wage equation, estimate β_d will show the direction of effect of intensity of job training. Precisely, it allows us to test if long time job training is providing positive effect on wage and if it is, then how much it would be.

In addition, I take into account the information of payer of cost of job training in wage equation. In fact, according to research on job training survey[9], there is the strong tendency that female trainee is most likely pay themselves for getting into the job training program. Since it is hard to find the selection process of job training especially for female explicitly, it would be possible to take this variable as a proxy of motivation of job training. Motivation affect the wage through the job training itself, thus when we estimate coefficient of β_d , it would be unlikely the true effect of job training, because a trainee with high motivation would be get high wage without training program. Hence it is possible to capture unobservable motivation among the female trainees so that it helps us to close to the true effect. This hypothesis would be tested by estimating wage equation that include variable that indicates history of payer of cost of job training. Tactically, I create a variable, ratio of number of times that one has paid the cost of job training by herself and number of times of job

[9]Kim, huel-he., Youn S Na and San D Lee, 2006, “The Proposal for Reducing the Gender Gap of Job Training”,*Working Paper serie* in KRIVET.

training during years that I examine in this paper.

Although I explore the applied fixed effect model in order to get rid of unobservable individual characteristic (correlated individual heterogeneity) as well as potential selection problem which involved with a fixed component, α_i, it still remains the problem if α_i is correlated with selection process. More precisely,

$$(a) \qquad Y_{it} = \alpha_i + \beta_x X_{it} + \varepsilon_{it} \; ; \; i = 1, ..., N, \; t = 1, ..., T$$
$$(b) \qquad d_{it}^* = \gamma_z Z_{it} + \eta_i + u_{it} \; ; \; d_{it} = 1 \; [if \;\; d_{it}^* > 0]$$

Above two equations express the hypothetical wage equation (a) and identified selection process. The variable Y_{it} is only observed if $d_{it}=1$. In order to get consistent estimates with using fixed effect model, it has to be satisfied with two following conditions;

$$(c) \qquad E(\alpha_i + \varepsilon_{it} \mid X_{it}, d_{it} = 1) = E(\alpha_i \mid X_{it}, d_{it} = 1) + E(\varepsilon_{it} \mid X_{it}, d_{it} = 1) = 0, \quad \forall t.$$
$$(d) \qquad E(\varepsilon_{it} - \varepsilon_{is} \mid X_{it}, X_{is}, d_{it} = d_{is} = 1) = 0, \qquad s \neq t$$

If these two conditions are violated, then it is difficult to get the consistent estimates from fixed effect model with using panel data. In this matter, Wooldridge (1995) has suggested one of the solutions for this problem. The idea of the estimator by Wooldridge is to derive an expression for the expected value in (c), and add it as an additional regressor to the wage equation. It is similar to Heckman's two-step estimator with Inverse mill's ratio (IMR). This is possibly applicable in my concern of wage equation in this paper. It is highly possible that decision process of labor attachment is related with individual fixed component in main wage equation. Therefore finally I estimates IMR, λ_{it}, from each year through the probit model and then add them into the wage equation. I could examine if this variable works very well in my wage equation through with checking the estimate coefficient of IMR.

The last wage equation that finally I will use for evaluating job training effect is following;

$$(4) \quad Y_{i98,05} = \alpha_i + \beta_x X_{i98,05} + \beta_d JT\_Days_{i98,05} \cdot Yr05 + \beta_{yr} Yr05 + \delta_1 \lambda_{it} + \delta_2 \lambda_{it} \cdot Yr05 + \varepsilon_{i98,05}$$

In this equation, X_{it} includes education level, industry, occupation information as well as several interaction terms. In next session, I describe more precisely detail variables that I have in wage equation.

III-2. Data & Descriptive Statistics

In this paper, I utilize the 8 years of panel data, Korea Labor & Income Panel Study (KLIPS) from 1998 to 2005. In order to make balanced panel, I match the individuals in 1998 and 2005 and it consist of female in age 16-66.

[Table 1] shows all the variable and definition of variable that I use in wage equation. In addition to these variables, I use several the interaction terms in wage equation. These interaction terms would help us to interpret the reactions between job training and industry or occupational variable.

[Table 2] & [Table 3] show the descriptive statistics for dependentand independent variables in treat group as well as controlled group in each year. There are several facts that I would like to mention from these tables. First,average age in treated group is younger than controlled group in 1998 and this propensity held in 2005. It implies age is still an important fact that affects the job training decision. The second, over all the education level in treated group is higher than controlled group given same age in 1998 as well as 2005. More precisely female who completed college or post college is more likely got job training but people who completed the secondary school slightly higher in controlled group. From this fact, it seems that education level could affect the decision of female in participation of job training as we expect. Thirdly,in 1998 it is quite clear that unmarried people tended to attend the job training rather than married female, however in 2005 this tendency was changed slightly. That is, percentage of unmarried female in treated group became declined in 2005 but proportion of married female was getting increased in 2005. It implies that the opportunity of job training has been extended among the female population, furthermore marriage status would less matter in decision of job training than we expect. The forth, interestingly the characteristic of family, number of family members, number of child in different age was not quite different in treated group and controlled group. Rather the proportion of number of child is little higher in treated group both of years. It might be reason for this consequence that the female who is able to use other child care system in outside of family can get the job training and this female is more likely have more child than one who is not affordable. The fifth, industry and occupation was not matter in female job training in 1998, in fact the proportion of female is higher in controlled group over all the industry and occupation categories in 1998. In 2005, however, this has changed in a sense that female in treated group tend to be in most of industry and occupations except industry 2 & 3, manufacture & construction, respectively, and simple work category. It implies that over the time, female job training has enlarged through the specific industries and occupation.

[Table 1 : Variables and Definitions]

Variable	Definition
lnWAGERATE	Natural logarithm of the hourly wage rate (won) in 1998 & 2005
lnJT_DAYS	Natural logarithm of the total days of job training that one have been taking in any year during 1999 & 2004
Ratio_CT_JT	Proportion of number of times that one paid cost of job training by herself and number of years of job training that one have taken during 1999 & 2004
Yr05	Dummy variable, =1 if year equals 2005; =0 if year equals 1998
Age	Age in years as of 1998 & 2005 survey date
Age_sq	Squared of Age
EDU_prim	Dummy variable, =1 if one completed primary school; =0 otherwise.
EDU_sec	Dummy variable, =1 if one completed secondary school; =0 otherwise.
EDU_coll	Dummy variable, =1 if one completed college school (2 or 4 years); =0 otherwise.
EDU_upcoll	Dummy variable, =1 if one completed post college school; =0 otherwise.
Marriage1	Dummy variable, =1 if one is not married; =0 otherwise.
Marriage2	Dummy variable, =1 if one is married; =0 otherwise.
N_fm	Number of family members
N_ch3	Number of children under age 4
N_ch7	Number of children under age 8
N_ch17	Number of children under age 18
Hhousehold	Dummy variable, =1 if one is head of household; =0 otherwise.
Employ Type	Dummy variable, =1 if current job is a irregular job; =0 otherwise
N_employed	Number of years of being employed during 1999 & 2004
IND1	Dummy variable, =1 if Industry is Agriculture; =0 otherwise.
IND2	Dummy variable, =1 if Industry is Manufacture; =0 otherwise.
IND3	Dummy variable, =1 if Industry is Construction; =0 otherwise.
IND4	Dummy variable, =1 if Industry is Transportation; =0 otherwise.
IND5	Dummy variable, =1 if Industry is Finance; =0 otherwise.
IND6	Dummy variable, =1 if Industry is Service; =0 otherwise.
OCC1	Dummy variable, =1 if occupation is a Professional job; =0 otherwise.
OCC2	Dummy variable, =1 if occupation is a Technician; =0 otherwise.
OCC3	Dummy variable, =1 if occupation is an Officer ; =0 otherwise.
OCC4	Dummy variable, =1 if occupation is a Service job; =0 otherwise.
OCC5	Dummy variable, =1 if occupation is a Producer ; =0 otherwise.
OCC6	Dummy variable, =1 if occupation is a Simple work; =0 otherwise.

[Table 2 : Descriptive statistics in Treated group vs. Controlled group in 1998]

	1998									
	Treated group					Controlled group				
Variable	Obs.	Mean	Std.	Min	Max	Obs.	Mean	Std.	Min	Max
Wage Rate	153	0.585	0.346	0.111	2.5	799	0.408	0.392	0.030	6.25
lnWAGERATE	153	-0.681	0.539	-2.202	0.916	799	-1.085	0.567	-3.514	1.832
Age	460	30.020	10.193	16	60	3511	37.754	12.224	16	60
Age_sq	460	1004.85	690.980	256	3600	3511	1574.77	940.87	256	3600
EDU_prim	460	0.0261	0.1595	0	1	3511	0.177	0.381	0	1
EDU_sec	460	**0.543**	0.499	0	1	3511	**0.606**	0.489	0	1
EDU_coll	460	**0.420**	0.494	0	1	3511	**0.175**	0.380	0	1
EDU_upcoll	460	**0.011**	0.104	0	1	3511	**0.006**	0.077	0	1
Marriage1	460	**0.463**	0.499	0	1	3511	0.216	0.411	0	1
Marriage2	460	0.502	0.500	0	1	3511	**0.710**	0.454	0	1
N_fm	460	**4.165**	1.185	1	8	3511	**4.066**	1.232	1	9
N_ch3	460	**0.215**	0.488	0	2	3511	**0.170**	0.434	0	2
N_ch7	460	**0.159**	0.399	0	2	3511	**0.148**	0.399	0	3
N_ch17	460	**0.733**	0.938	0	3	3511	**0.843**	0.964	0	5
Hhousehold	460	**0.076**	0.265	0	1	3511	**0.082**	0.274	0	1
IND2	460	0.057	0.231	0	1	3511	0.063	0.243	0	1
IND3	460	0.013	0.114	0	1	3511	0.008	0.087	0	1
IND4	460	0.061	0.240	0	1	3511	0.058	0.232	0	1
IND5	460	0.050	0.218	0	1	3511	0.019	0.138	0	1
IND6	460	0.140	0.346	0	1	3511	0.067	0.250	0	1
OCC1	460	0.076	0.265	0	1	3511	0.014	1.117	0	1
OCC2	460	0.067	0.251	0	1	3511	0.026	0.159	0	1
OCC3	460	0.102	0.303	0	1	3511	0.053	0.224	0	1
OCC4	460	0.043	0.204	0	1	3511	0.052	0.223	0	1
OCC5	460	0.017	0.131	0	1	3511	0.033	0.178	0	1
Employ Type	460	**0.072**	0.258	0	1	3511	**0.099**	0.298	0	1
N_employed	460	**3.508**	1.923	0	6	3511	**2.259**	2.092	0	6
JT_DYAS	460	103.6239	161.189	1	1210					
lnJT_DAYS	460	3.289	1.857	0.693	7.099					
Ratio_cost_JT	460	0.368	0.459	0	1					
Total Obs.	3971					3971				

[Table 3 : Descriptive statistics in Treated group vs. Controlled group in 2005]

	2005									
	Treated group					Controlled group				
Variable	Obs	Mean	Std.	Min	Max	Obs	Mean	Std.	Min	Max
WAGE RATE	244	0.943	0.560	0.167	4.000	995	0.606	0.509	0.067	8.688
lnWAGERATE	244	-0.220	0.574	-1.792	1.386	995	-0.675	0.546	-2.701	2.162
Age	466	36.729	10.195	22	66	3476	44.047	12.067	22	66
Age_sq	466	1452.78	823.414	484	4356	3476	2085.73	1074.95	484	4356
EDU_prim	466	0.028	0.165	0	1	3476	0.171	0.377	0	1
EDU_sec	466	**0.448**	0.498	0	1	3476	**0.548**	0.498	0	1
EDU_coll	466	**0.489**	0.500	0	1	3476	**0.232**	0.422	0	1
EDU_upcoll	466	**0.034**	0.182	0	1	3476	**0.018**	0.131	0	1
Marriage1	466	0.307	0.462	0	1	3476	0.143	0.350	0	1
Marriage2	466	0.631	0.483	0	1	3476	0.742	0.438	0	1
N_fm	466	**3.639**	1.147	1	7	3476	**3.573**	1.212	1	10
N_ch3	466	**0.131**	0.412	0	2	3476	**0.081**	0.292	0	2
N_ch7	466	**0.122**	0.371	0	3	3476	**0.107**	0.345	0	2
N_ch17	466	**0.770**	0.914	0	3	3476	**0.674**	0.927	0	5
Hhoushold	466	**0.148**	0.356	0	1	3476	**0.149**	0.356	0	1
IND2	466	0.058	0.234	0	1	3476	0.094	0.291	0	1
IND3	466	0.006	0.080	0	1	3476	0.008	0.089	0	1
IND4	466	0.238	0.426	0	1	3476	0.169	0.375	0	1
IND5	466	0.056	0.230	0	1	3476	0.014	0.117	0	1
IND6	466	0.354	0.479	0	1	3476	0.148	0.356	0	1
OCC1	466	0.163	0.369	0	1	3476	0.039	0.193	0	1
OCC2	466	0.114	0.318	0	1	3476	0.046	0.209	0	1
OCC3	466	0.165	0.372	0	1	3476	0.063	0.243	0	1
OCC4	466	0.225	0.418	0	1	3476	0.157	0.363	0	1
OCC5	466	0.041	0.198	0	1	3476	0.107	0.310	0	1
Employ Type	466	0.127	0.333	0	1	3476	0.137	0.344	0	1
N_employed	466	**3.487**	1.929	0	6	3476	**2.260**	2.089	0	6
JT_DAYS	466	105.217	163.093	1	1210					
lnJT_DAYS	466	3.301	1.863	0.693	7.099					
Ratio_cost_JT	466	0.372	0.461	0	1					
Total Obs.	3942									

Finally the years of employed during the years (1999-2004) is higher in treated group than controlled group. Through this fact, we can guess that two implications, job training has increased female's labor participation rate or employed female has more chances to get job training. These two different directions related with job training and female labor attachment is important issue that needs to discuss on inference of job training and the effect of it. I will try to discuss this matter later in this paper.

[Table 4] indicates the number of participants of female & male during 6 years in KLIPS data set. As we can see the number of the participants of female in job training in both specific and general has been increased over the year. However, it is clear that the number of participants of female is quite less than one of male. Because of this small number of female trainee in this data become troublesome to get the inference of effect of job training of female. As I mention before, the one way to solve out this problem of small sample size is to accumulate the years for job training and compare two year, before & after job training years, that do not have job training experience. In doing so, I can increase the sample size of treated group. Even though this strategy lose the chance to use advantage of dynamic analysis with using complete panel data set, it is meaningful to see the effect of job training with control the individual characteristics. Following session, I show the several results from different econometric specification of wage equations and discuss about the effect of them.

[Table 4: Number of Participants in Job Training in Each Year]

(Unit: Person, %)

years	Participants in Job Training				Total Obs. in Data set	
	Female		Male			
	Numbers	%	Numbers	%	Numbers	%
1999	75	1.67	118	2.72	4806|4338	100
2000	67	1.39	129	2.97	4806|4338	100
2001	141	2.93	227	5.23	4806|4338	100
2002	156	3.24	236	5.44	4806|4338	100
2003	147	3.06	264	6.08	4806|4338	100
2004	186	3.87	322	7.42	4806|4338	100
Total[1)]	467	9.71	652	15.02	4806|4331	100

Notice: 1) Cumulative total during the years from 1999 to 2004

III-3. Empirical Results of Estimates of job training on Female Wage

Before take a look at the main results, it is worthwhile to see the simple difference of wage rate in before and after the job training periods. [Table 5] is constructed by the average wage rate from descriptive statistics that I have explained. This table helps us to get intuition of dif-n-dif methodology. As we can see, with dealing of group specific and time specific effect, the job training of female has positive effect, 0.160 on wage rate. In other words, if a female got job training any year during 1999 & 2004, she might increase the wage rate up to 1600 won. Obviously it is extremely simple to interpret the effect because there should be other factors that we have to consider in this matter. With having rough sense of this result, I apply other specification that let other factors in wage equation.

[Table 5: Simple differences in wage rate before (1998) and after (2005)]

(Unit: 10000 won)

	Wage Rate (Average Level)[1]		Dif-n-Dif
	Before (1998)	After (2005)	
Treated group (Have been in job training programs during years)	0.585	0.943	
Controlled group (Have not even been in job training program during years)	0.408	0.606	
Difference between treated & controlled group	**0.177**	**0.337**	**0.16**

Notice: 1) Average hourly wage in each year.

[Table 6] shows the result of estimates from different specification of wage equation that I supposed in previous sessionin this paper. First, column 1indicates the OLS estimator without fixed effect. As we can see the effect of job training is positive and statistically significant in 5 % level. It means if a female increase 1 % point of days in any job training during 6 years it could increase her wage rate up to 3.5%. In this specification, year effect also has strong positive effect on wage rate. In addition, we can see the returns of education is quite high in higher education level, and as we can expect having irregular job has strong and significant negative effect on female wage. Even this OLS estimates indicates typical results, it has not controlled the unobserved individual characteristics. The column2 is basic fixed effect model without any othercovariates. In this specification, the coefficient of days of job training is even higher than OLS estimator and it is statistically significant. And the year effect also held in this model. However, once we add other covariates it shows different result. Column 3, 4, and 5 are the results of estimates with different covariates in the model.

[Table 6: Results of The Estimates of Effect of Job training on WAGE]

		Simple OLS	Fixed Effect						Fixed Effect with IMR
	Specifications	1	2	3	4	5	6	7	8
lnWAGERATE									
lnJT_DAYS*Yr05	Coef.	0.0346**	0.0517**	0.0344*	0.0395**	0.0466**	0.0463**	0.0538*	0.0494*
	(t-value)	(4.82)	(2.8)	(1.9)	(2.19)	(2.32)	(2.28)	(1.82)	(1.66)
Yr05		0.3709**	0.5133**	0.8258	-0.5293	-0.1864	-0.4738	-0.4668	-0.4941
		(17.49)	(17.69)	(0.21)	(-0.14)	(-0.05)	(-0.12)	(-0.12)	(-0.12)
Age		0.0558		0.0486	0.2370	0.1886	0.2280	0.2269	0.2315
		(8.93)		(0.09)	(0.42)	(0.34)	(0.4)	(0.4)	(0.41)
Age_sq		-0.0006**		-0.0012**	-0.0011**	-0.0011**	-0.0011**	-0.0011**	-0.0010**
		(-8.05)		(-6.17)	(-5.79)	(-5.74)	(-5.61)	(-5.59)	(-4.65)
EUD_sec		0.0852**		0.0822	0.2575	0.2923	0.3010	0.3022	0.2962
		(2.5)		(0.25)	(0.79)	(0.89)	(0.91)	(0.91)	(0.89)
EDU_coll		0.3550**		-0.0306	0.1754	0.2126	0.2199	0.2218	0.2107
		(7.98)		(-0.09)	(0.5)	(0.6)	(0.62)	(0.62)	(0.59)
EDU_upcoll		0.8708**		0.1848	0.3957	0.3826	0.3908	0.4083	0.3893
		(10.61)		(0.48)	(1.01)	(0.97)	(0.99)	(1.03)	(0.98)
IND2		0.0062			0.0151	0.0274	0.0288	0.0269	0.1015
		(0.11)			(0.15)	(0.27)	(0.28)	(0.26)	(0.6)
IND3		0.2777**			0.0287	0.0661	0.0844	0.0870	0.1706
		(3.53)			(0.17)	(0.35)	(0.45)	(0.47)	(0.74)
IND4		0.1053			0.0654	0.0749	0.0886	0.0897	0.1802
		(1.81)			(0.56)	(0.6)	(0.71)	(0.72)	(0.95)
IND5		0.3609**			0.2637	0.3592**	0.3844**	0.3874**	0.4603**
		(5.27)			(1.7)	(2.14)	(2.28)	(2.3)	(2.08)
IND6		0.1186**			-0.0001	0.0463	0.0746	0.0744	0.1484
		(2.11)			(0)	(0.39)	(0.63)	(0.62)	(0.79)
OCC1		0.4251**			0.1251	0.1494	0.1210	0.1130	0.1392
		(8.64)			(0.95)	(1.04)	(0.84)	(0.78)	(0.94)
OCC2		0.3443**			0.2335**	0.1809	0.1566	0.1525	0.1799
		(7.66)			(2.12)	(1.51)	(1.28)	(1.24)	(1.44)
OCC3		0.2800**			0.0044	-0.0370	-0.0771	-0.0789	-0.0655
		(7.03)			(0.04)	(-0.33)	(-0.66)	(-0.68)	(-0.55)
OCC4		-0.0635*			-0.1748**	-0.1703**	-0.1694**	-0.1694**	-0.1370
		(-1.76)			(-2.19)	(-2.00)	(-1.99)	(-1.99)	(-1.55)
OCC5		0.0314			-0.0355	-0.0287	-0.0471	-0.0475	-0.0200
		(0.82)			(-0.45)	(-0.35)	(-0.57)	(-0.57)	(-0.21)

lnJT_Days*IND2					-0.0469	-0.0501	-0.0584	-0.0538
					(-0.39)	(-0.41)	(-0.47)	(-0.44)
lnJT_Days*IND3					-0.1493	-0.1623	-0.1753	-0.1700
					(-0.84)	(-0.91)	(-0.97)	(-0.94)
lnJT_Days*IND4					-0.0969	-0.1011	-0.1010	-0.1010
					(-0.71)	(-0.73)	(-0.73)	(-0.73)
lnJT_Days*IND5					-0.2610	-0.2699*	-0.2731*	-0.2713*
					(-1.58)	(-1.63)	(-1.65)	(-1.64)
lnJT_Days*IND6					-0.1731	-0.1788	-0.1842	-0.1842
					(-1.25)	(-1.29)	(-1.3)	(-1.3)
lnJT_Days*OCC1					0.0243	0.0630	0.0605	0.0612
					(0.2)	(0.49)	(0.46)	(0.47)
lnJT_Days*OCC2					0.0779	0.1098	0.1080	0.1094
					(0.67)	(0.92)	(0.91)	(0.92)
lnJT_Days*OCC3					0.0818	0.1296	0.1249	0.1273
					(0.68)	(1.02)	(0.97)	(0.99)
lnJT_Days*OCC4					0.0417	0.0753	0.0670	0.0740
					(0.41)	(0.7)	(0.62)	(0.68)
lnJT_Days*OCC5					-0.0811	-0.0410	-0.0389	-0.0388
					(-0.61)	(-0.3)	(-0.28)	(-0.28)
lnJT_Days*Emp_Type						-0.0273	-0.0226	-0.0242
						(-0.49)	(-0.38)	(-0.41)
Employ_Type	**-0.13283****					-0.0874*	-0.0883*	-0.0777
	(-6.06)					(-1.64)	(-1.65)	(-1.44)
N_employed*Yr05						0.0019	0.0022	0.0012
						(0.11)	(0.13)	(0.07)
Selfpay*Yr05							-0.2888	-0.2163
							(-0.7)	(-0.52)
lnJT_Days*Selfpay*Yr05							0.0402	0.0313
							(0.44)	(0.34)
Lambda								0.0750
								(0.69)
Lambda*Yr05								-0.1911
								(-1.35)
Constant	**-2.4888****	**-1.0865****	-1.2466	-7.9237	-6.2630	-7.5839	-7.5394	-7.8914
	(-19.5)	(-62.98)	(-0.07)	(-0.42)	(-0.33)	(-0.39)	(-0.39)	(-0.41)
No. Obs	2219	2219	2219	2219	2219	2219	2219	2191
No. Groups		1745	1745	1745	1745	1745	1745	1717
R-squared	0.46	0.47	0.51	0.54	0.55	0.55	0.56	0.56

Without dummy variables of industry and occupation, the effect is getting decrease and even less significant. But once add industry and occupational dummy variables, the estimate of job training get significant. With this result we could suspect the relationship between job training and industry & occupation. In order to clarify this relationship, I add the interaction term. Interestingly, the coefficient of job training is even higher and stronger than without interaction terms. But any of the coefficients of interaction terms is not significant.

In Column 6, I include employed type and interaction term with job training to see the effect of job training and irregular job in female labor market. Estimate of job training does not change much. And having a irregular job has a negative effect on wage rate as same as before but coefficient of interaction term is quite small and insignificant. It implies that it is hard to claim that female job training leads to provide irregular job to female labor at least through the data set I utilized here.

The Column 7 shows the result with ratio of self payer of cost of job training. I add this variable with intention of dealing with unobservable motivation among the female job trainees. In this specification, the coefficient of job training becomes higher but it loses significance. About the estimated coefficients of ratio of self payer of cost of job training and interaction term, former one has negative sign and latter one has positive sign. However, both of them are not significant. These result is quite different from what I expected before, even more difficult to interpret this result. It might be true that self payer of cost of job training does not play as a indicator of motivation but it does play a signal of poor skilled labor involved with short term job training. Thus it has negative relationship with wage and it could take some part of negative effect from job training on wage. Therefore, it increases the effect of long term job training.

Finally, last column shows the result with IMR that I have got from each year. Each IMR is created from Probit model in each year[10]. When I add these variables in wage equation, the estimated coefficient of job training becomes lower and less significant than without these variables but still 10% level significant. IMR for over the year has positive coefficient and IMR from only 2005 has negative one. Even if these IMRs are not significant in 10% level, it could help to understand the current situation of female labor and labor market in general. That is, it could be interpreted in sense that the propensity of participation rate of labor force in over the year has positive effect on wage rate of female, but one of 2005 has negative effect on wage rate. In other words, even if female labor participation rate has been increase in 2005 but it does not help female to get a higher wage, possibly female got indecent job. Therefore the effect on wage rate indicates negative. Other than this, the specification with IMRs does not seem work very well that I expect.

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[10] I put the result of Probit model in each year in the appendix in the last page of this paper.

IV. Conclusive Remarks

Theoretical considerations of job training suggest enough reasons why job training is important in labor market. It would be more crucial for female, because female used to be in weaker position in labor market and job training of female would be one of the implements compromise or moderate labor market that tend to be in favor of male. In order to support this proposition, it would be the first step where providing accurate measure of effect of current job training in Korea.

In this paper I estimated job training effect of Korean female, using applied fixed effect model with 8 years of panel data. Even if I utilize 8 years panel data, it is hard to get enough sample size for measuring effect of job training for female. To avoid this problem I modify the dif-n-dif methodology with taking advantage of fixed effect model. I define the treated group in which female has got job training program in any year during 1999 and 2004. Thus this strategy gave reasonable sample size for doing this research. In addition, in order to indicate the effect intensity of job training, I use accumulative days that female has taken for job training rather than simple dummy variable that indicate experience of job training.

With various specification of wage equation I have got interesting results of female job training effect. First, the fixed effect model for wage equation of Korean female gives even stronger effect of job training. With covariates, age, age-squared, dummy variables of several education level, industry & occupation, and type of employed the estimated coefficient of job training is 0.0466 and it is statistically significant in 5% level. It means if one female has got 1% of day of job training, she would get 4.6% increase of her wage. Second, adding self-pay of cost of job training as a proxy of measuring motivation increase the level of coefficient (0.053) with losing significance. However, the estimated coefficient of job training is still significant at 10% level. Unfortunately, self-pay of cost of job training is not a good proxy of motivation of female participants in job training. Rather it indicates a signal of a poor skilled labor who tends to have short term job training. Obviously it has a negative relationship with wage.

Third, to deal with selection problem in panel data, I adopt the suggestion from Wooldridge's work. With using Probit model, I have got the inverse mill's ratio from each year, 1998 and 2005, and add them on the wage equation. In this specification, the estimated coefficient of job training and significance get lower than without IMRs. In this last specification, the effect of job training is 0.049 and it implies if one female got 1% point of days of job training, her wage would be increased up to 4.9 %. Since the estimate of coefficient of each IMR is not statistically significant, it is hard to say this model works very well for eliminating the self selection problem in the wage equation. However, direction of each coefficient of IMR in wage equation would provide important implication over the Korean female labor market. That is even though female participation rate of labor force increase during years, but it does not mean that female has more earning than before. It would be possible having job contaminates their structure of earning in labor market. Negative coefficient of IMR from 2005 shows it implicitly.

Even if I was able to measure the cumulative effect of job training, it still remains the several problems. Especially, distinguishing of effects of firm specific and general job training is necessarily needed to be developed. It would help to get more accurate effect of job training especially for female. It is true that it would challenge us given limit of available data but it would be an important future work has to be done.

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[Appendix I : Result of Probit Regression in 1998]

Probit Regression in 1998

	Coefficient	Std. Err.	z	P>|z|
Age	0.05866	0.039795	1.47	0.14
Age_sq	-0.00073	0.000501	-1.47	0.142
EDU_sec	0.000715	0.15524	0	0.996
EDU_coll	-0.33407	0.229125	-1.46	0.145
EDU_upcoll	-0.31916	0.863078	-0.37	0.712
IND2	3.658786	0.200936	18.21	0
IND3	2.949835	0.398403	7.4	0
IND4	3.043269	0.222024	13.71	0
IND5	3.296847	0.392095	8.41	0
IND6	3.329989	0.204092	16.32	0
OCC1	8.879103	.	.	.
OCC2	0.977674	0.310708	3.15	0.002
OCC3	1.557383	0.244833	6.36	0
OCC4	1.523614	0.249352	6.11	0
OCC5	3.120641	0.29398	10.62	0
lnJT_Days	0.049931	0.066778	0.75	0.455
lnJT_Days*Selfpay	-0.27086	0.167689	-1.62	0.106
Selfpay	0.630519	0.622047	1.01	0.311
Marriage2	-0.10253	0.162446	-0.63	0.528
N_fm	-0.15936	0.046068	-3.46	0.001
N_ch3	-0.2351	0.157669	-1.49	0.136
N_ch7	-0.06529	0.154797	-0.42	0.673
N_ch17	0.063411	0.082905	0.76	0.444
Constant	-2.59475	0.747419	-3.47	0.001
mills				
lambda	0.158125	0.065781	2.4	0.016
rho	0.33272			
sigma	0.475241			
lambda	0.158125	0.065781		
No. Obs	4113			
Loglikelihood	-314.049			
Lagrange Ratio (chi2 (23))	3934.56		(Prob. > Chi2 =0)	
Pusuedo R2	0.8623			

[Appendix II : Result of Probit Regression in 2005]

Probit Regression in 2005		Coefficient.	Std. Err.	z	P>|z|
	Age	-0.0826	0.026169	-3.16	0.002
	Age_sq	0.000626	0.000303	2.07	0.039
	EDU_sec	-0.27688	0.108386	-2.55	0.011
	EDU_coll	-0.28306	0.13975	-2.03	0.043
	EDU_upcoll	-0.24685	0.239527	-1.03	0.303
	IND2	4.0773	0.186106	21.91	0
	IND3	4.101528	0.322243	12.73	0
	IND4	3.692116	0.173101	21.33	0
	IND5	3.254797	0.222324	14.64	0
	IND6	4.050392	0.167194	24.23	0
	OCC1	-0.7565	0.161881	-4.67	0
	OCC2	-0.97315	0.15136	-6.43	0
	OCC3	-0.18604	0.151332	-1.23	0.219
	OCC4	-1.05201	0.125996	-8.35	0
	OCC5	-0.33964	0.151565	-2.24	0.025
	lnJT_Days	0.112101	0.034414	3.26	0.001
	lnJT_Days*Selfpay	0.060851	0.079111	0.77	0.442
	SelfPay	-0.81195	0.316772	-2.56	0.01
	Marriage2	-0.27271	0.088327	-3.09	0.002
	N_fm	-0.02969	0.029278	-1.01	0.311
	N_ch3	-0.03574	0.131896	-0.27	0.786
	N_ch7	-0.14781	0.108322	-1.36	0.172
	N_ch17	0.024292	0.045033	0.54	0.59
	Constant	0.067315	0.526239	0.13	0.898
mills					
	lambda	0.09486	0.153837	0.62	0.537
	rho	0.21186			
	sigma	0.447758			
	lambda	0.09486	0.153837		
	No. Obs.	4086			
	Loglikelihood	-1062.97			
	Lagrange Ratio (Chi2(23))	3024.3		(Prob. > chi2 = 0)	
	Pseudo R2	0.5872			