Industry-Specific Human Capital and the Wage Profile: Evidence from Taiwan

Yih-chyi Chuang and **Chun-yuan Lee**

National Chengchi University, Taipei; Tamkang University, Taipei

Abstract: Using data from Taiwan's Manpower Utilization Survey (1979–2000), this paper finds evidence that supports the industry-specific human capital effect on wage tenure profiles. Work experience is used as an indirect measure for testing industry-specific human capital by comparing the effect between stayers and movers. Other things being equal and holding firm tenure constant, movers actually incur a wage loss measured by the wage premium of the work experience. However, a greater than average firm tenure effect, especially for movers in the voluntary group, reflects an underlying job-related matching process. We also find that the effect of work experience declines with education, while the effect of industry-specific human capital increases with education. JEL no. J24, J31, J41, J62
Keywords: Industry-specific human capital; job matching; on-the-job training

1 Introduction

Ever since the seminal works by Schultz (1961), Becker (1975), and Mincer (1974), human capital has been identified as a crucial factor in determining one's productivity and hence an important factor in production and growth. The accumulation of human capital can be formed through channels such as formal education, on-the-job training, learning-by-doing, and improvement in health and nutrition. Among different forms of accumulation, numerous studies have found the importance of on-the-job training for workers to gain and accumulate new skills, which in turn show up in an increase of his or her wages. Conventionally, on-the-job training is classified into two types, general training and firm-specific training (Becker 1975). Empirically, the effect of on-the-job training is measured by the wage gain with years of work experience.

The worker's total labor market experience can accordingly be decomposed into two components, tenure with the current employer and general

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Remark: Please address correspondence to Yih-chyi Chuang, Department of Economics, National Chengchi University, Taipei 116, Taiwan, ROC; e-mail: ycchuang@nccu.edu.tw

work experience. However, recent research by Kim (1998), Kletzer (1996), Neal (1995), Parent (2000), and Weinberg (2001) find that industry-specific skills may constitute an important component of the typical worker's human capital stock. Using U.S. Displaced Workers' Survey data, Neal (1995) discovers that the wage cost of switching industries following displacement is strongly correlated with predisplacement measures of both work experience and tenure. Weinberg (2001) also finds that the postdisplacement wages of displaced workers are strongly affected by demand in their predisplacement industries.

Using data from the National Longitudinal Survey of Youth (1979–1996) and Panel Study of Income Dynamics (1981–1991), Parent (2000) shows that by including total experience in the industry as an additional explanatory variable, the return on seniority is markedly reduced. All these findings suggest that what matters most for the wage profile in terms of human capital is industry specificity, not firm specificity. This paper intends to test the hypothesis of the importance of industry-specific human capital in determining worker's wage profiles using Taiwan's labor market data and tries to provide an explanation for the rapid job switch across industry in Taiwan.

This paper is organized as follows. Section 2 lays out the empirical model and modeling strategy to disentangle the effect of industry-specific human capital under the limited information available from Taiwan's labor market data. Section 3 describes the data used. Section 4 provides the two-stage estimation results. Finally, concluding remarks are followed in Section 5.

2 The Empirical Model

The conventional method in testing industry-specific human capital requires data on preswitching industry-specific tenure and preswitching wage to calculate wage loss due to switching from an industry (Neal 1995). Neither of this kind of data is available for Taiwan. Huang (2001) uses the probability of staying in the same industry to calculate the expected length of time spent in one's last industry. This method implicitly assumes that workers in the same industry have the same likelihood of switching an industry when they change jobs, and a person will not reenter an industry he or she worked before. Moreover, any interrupted experience in the same industry will not affect one's stock of industry-specific human capital. Under those assumptions, Huang (2001) finds little evidence of industry-specific human capital on wage determination in Taiwan.[1]

Incorporating industry-specific human capital, the traditional wage equation is modified and formulated as:

$$\begin{aligned} W = {} & \mu(\textit{experience}) + \phi(\textit{industry tenure}) \\ & + \gamma(\textit{firm tenure}) + X\beta + \varepsilon. \end{aligned} \tag{1}$$

However, due to lack of data on preswitching industry tenure, the empirical strategy of this paper implicitly infers the effect of industry-specific human capital by examining the returns on work experience and firm tenure between stayers and movers who change jobs on the postswitching wage. Stayers are workers who remain in the same industry after changing a job, while movers are workers who switch industry after changing a job. Wages of stayers and movers are determined according to (2) and (3):

$$W_s = \alpha(\textit{experience}) + \gamma(\textit{firm tenure}) + X\beta + \varepsilon_s, \tag{2}$$

$$W_m = \delta(\textit{experience}) + \gamma(\textit{firm tenure}) + X\beta + \varepsilon_m, \tag{3}$$

where subscript s denotes stayers, m stands for movers, and X is a vector of worker's characteristics. As work experience includes general experience and industry tenure if industry-specific human capital does not matter (i.e., $\phi = 0$ in (1)), then α in (2) should equal δ in (3). If α is greater than δ, this implies that there exists industry-specific human capital that increases the return on work experience, which includes general experience as well as industry-specific experience.

We can alternatively run the following regression:

$$\begin{aligned} W = {} & \lambda(\textit{experience}) + \gamma(\textit{firm tenure}) \\ & + \theta(\textit{IND} \times \textit{experience}) + X\beta + \varepsilon, \end{aligned} \tag{4}$$

where *IND* is a dummy, 1 for stayers and 0 for movers. Term θ is expected to be positive in the presence of industry-specific human capital. In sum, for stayers the work experience carries over industry tenure, while for movers the work experience is a pure general experience. Empirically, our test of industry-specific human capital is based on (4), however, we also treat the stayers and movers as two distinct groups and perform the test according to (2) and (3).

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[1] Using industry tenure data from Taiwan Women and Family Survey, Huang (2003) also finds little evidence of industry-specific human capital on wage determination in Taiwan.

As job change is apparently a self-selection choice, sample selection bias may encounter in doing the wage regressions. However, we only do the selection for movers and stayers but do not do the selection for people who change jobs versus who do not. The reason is that in our study whether stayers or movers they are job changers, i.e., they all had changed job. As they are all job changes, what makes the selection different is the decision to switch an industry or to stay in the same industry.

Since our analysis is confined to job changers, for those job changers either movers or stayers were likely to share similar selection effects of job change even if the selection of job change did exist. Therefore, without controlling for job-change selection will not affect our conclusion by comparing the relevant estimated coefficients between movers and stayers. We adopt Heckman's (1979) two-stage estimation method to correct for the likely self-selection bias for stayers and movers. The first-stage regression is set up as

$$S = a_0 + a_1 GX + a_2 GX^2 + a_3 ED + a_4 Z + \nu, \tag{5}$$

where S is the job preference for switching industry which is an unobserved latent variable, GX is for work experience, ED is for education, and Z is a vector for worker's other characteristics. As for the sensitivity of the estimates to the exclusion restrictions used in the selection correction, we further perform a multinomial logit model to estimate the selection among workers who do not change job, workers who change job but stay in the same industry, and workers who change job and also switch industry. The estimation results remain the same as our previous mover-stayer correction. Therefore, our estimation results seem to survive under the exclusion restrictions used in the selection correction.[2]

3 The Data

The data used in this paper is from Taiwan's Manpower Utilization Surveys for the period 1979–2000. The MPUS data are repeated cross sections, stratified random samples of around 19,700 households from about 7,510 villages and neighborhoods of Taiwan, and they are not panel data. All the figures in the paper are in NT dollars with 1996 as the base year. Work

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[2] We thank one referee for pointing out a discussion of the exclusion restrictions used in the selection correction.

Table 1: *Basic Summary of Data, 1979–2000*

Years	Monthly averages of hourly wages (NT$)						Years of schooling					
	Privately employed workers	Job changers					Privately employed workers	Job changers				
		Whole changers	Voluntary		Involuntary			Whole changers	Voluntary		Involuntary	
			Stayers	Movers	Stayers	Movers			Stayers	Movers	Stayers	Movers
1979	56.62	51.61	58.42	48.61	56.19	50.58	8.09	8.41	8.34	8.71	7.43	7.03
1980	58.11	50.98	55.01	48.89	64.22	49.51	8.38	8.60	8.72	8.82	7.74	6.75
1981	62.66	57.82	66.06	54.41	64.97	58.38	8.49	8.99	8.98	9.23	8.51	7.44
1982	68.36	61.93	70.73	56.72	68.36	61.82	8.58	8.94	8.51	9.49	8.81	7.39
1983	71.51	60.91	65.77	58.03	76.94	56.08	8.77	9.21	9.01	9.60	8.37	7.74
1984	75.01	67.71	76.18	63.11	80.76	65.87	8.93	9.54	9.45	9.88	8.86	8.00
1985	77.46	70.14	77.37	66.82	73.40	67.01	8.98	9.74	10.01	9.89	8.65	8.06
1986	81.29	71.32	77.02	67.95	81.81	69.56	9.00	9.31	9.49	9.55	8.82	8.29
1987	83.93	73.86	77.38	71.96	79.80	70.90	9.29	9.84	9.84	10.11	9.40	8.45
1988	92.90	84.37	92.32	80.87	95.89	73.03	9.51	10.16	10.33	10.45	8.38	8.30
1989	104.93	95.28	103.14	90.94	104.95	88.75	9.64	10.12	10.42	10.37	8.49	8.56
1990	116.50	104.51	112.90	100.09	114.55	98.76	9.81	10.50	10.89	10.79	9.29	8.39
1991	123.89	110.93	126.64	104.75	113.34	99.59	9.92	10.50	10.74	10.75	9.17	9.11
1992	132.96	116.68	127.83	108.03	157.99	110.72	10.08	10.75	11.00	10.84	9.92	9.48
1993	141.85	129.14	150.49	120.65	142.42	107.68	10.20	10.87	11.26	10.97	9.90	9.58
1994	148.40	134.63	146.40	128.41	158.94	123.71	10.34	11.06	11.55	11.02	10.93	9.72
1995	152.05	132.47	142.60	124.41	149.59	139.32	10.53	11.26	11.49	11.14	11.30	11.19
1996	153.03	138.17	151.45	131.40	147.83	128.80	10.76	11.36	11.92	11.51	9.98	10.43
1997	154.23	142.59	147.50	134.96	193.79	123.50	10.89	11.60	12.13	11.73	10.44	10.11
1998	158.31	141.00	157.25	132.21	165.19	121.92	11.09	11.79	12.26	11.81	11.48	10.56
1999	160.38	138.98	150.69	135.24	162.44	115.29	11.31	11.72	12.13	12.02	11.00	10.11
2000	162.04	141.56	149.17	134.29	177.56	129.57	11.42	12.04	12.40	12.24	11.28	10.74
79–00	110.75	98.94	108.29	93.76	115.04	91.38	9.73	10.29	10.49	10.50	9.46	8.88

Table 1: *Continued*

Years	Years of work experience						Observations (male)					
	Privately employed workers	Job changers					Privately employed workers	Job changers				
		Whole changers	Voluntary		Involuntary			Whole changers	Voluntary		Involuntary	
			Stayers	Movers	Stayers	Movers			Stayers	Movers	Stayers	Movers
1979	13.16	12.82	11.97	11.02	17.72	25.05	8,678	1,030	245	618	43	124
1980	14.11	12.25	11.37	11.00	17.83	22.63	8,893	679	162	418	30	69
1981	14.61	11.93	11.69	10.77	14.69	19.98	9,605	865	226	529	22	88
1982	14.56	12.00	13.35	9.20	15.33	21.09	9,330	806	261	407	32	106
1983	14.37	11.52	11.75	9.49	19.28	20.33	9,124	838	231	477	40	90
1984	14.55	11.81	12.18	9.84	18.75	20.16	9,595	925	252	519	36	118
1985	14.56	11.47	10.80	10.34	17.90	20.19	9,741	955	268	581	25	81
1986	14.62	12.44	11.45	10.72	17.25	18.58	9,705	1,104	226	641	92	145
1987	14.79	12.04	11.94	10.23	18.58	19.40	10,333	1,040	290	579	58	113
1988	15.12	11.75	10.93	10.65	18.40	19.18	10,430	1,054	306	613	59	76
1989	15.43	12.31	10.93	11.25	18.18	20.51	10,448	1,012	277	579	66	90
1990	15.50	12.43	11.81	10.73	17.96	20.91	10,297	1,012	263	572	79	98
1991	16.17	12.17	11.34	10.47	18.75	21.08	9,974	790	217	445	55	73
1992	16.22	11.91	11.56	10.74	17.52	19.71	10,039	844	221	510	57	56
1993	16.41	12.73	12.02	11.50	18.66	19.41	11,065	977	271	575	56	75
1994	15.89	11.99	11.50	11.08	14.62	19.19	11,295	935	239	565	66	65
1995	15.93	11.98	11.75	11.17	16.58	16.20	11,284	748	222	429	50	47
1996	15.84	11.95	11.54	10.24	18.66	15.24	10,593	899	246	452	91	110
1997	16.02	12.17	10.97	10.74	18.46	18.65	10,666	777	220	399	74	84
1998	16.06	11.91	10.67	10.91	15.85	17.49	11,107	843	208	451	78	106
1999	15.74	11.92	10.28	10.64	18.03	16.77	10,930	745	182	388	71	104
2000	15.76	11.29	10.62	9.74	17.41	15.98	11,024	824	223	427	79	95
79–00	15.25	12.04	11.47	10.57	17.56	19.44	224,156	19,702	5,256	11,174	1,259	2,013

Note: Job changers are defined as workers who had changed jobs during the previous year. The workers who changed jobs during the current year are not counted as job changers. Job changers can be divided into stayers and movers: stayers are workers that do not switch an industry and movers are workers that switch an industry.

experience is calculated as age minus years of schooling minus 8 for males over 20 (6 for males under 20).[3] As female workers are likely to move in and out of labor market discontinuously due to marriage or child rearing, we only consider privately employed male workers in our study. As the survey only asked job changers whose job tenure were less than one and half years, our analysis is thus confined to workers with firm tenure less than one and half years.

There are two types of job change, voluntary and involuntary. Topel (1990), Gibbons and Katz (1991), and Neal (1995) point out that the productivity of these two types of workers is quite different, whereby on average, voluntary workers have a higher productivity than the involuntary ones. Hence, for an unbiasedness reason, in our estimation we separately test these two groups of workers.

According to MPUS definition, the voluntary changers are workers who have quitted a job at his/her own will. It may be due to reasons such as low pay, no job security, poor working environment, inadequate working time, etc. The involuntary changers are workers who left their last job not at his/her will, but under the regulations of the working place. It may be due to reasons such as a workplace shutting down or business shrinkage, a seasonal or temporary job being completed, layoff because of personnel reorganization, job relocation, mandatorily retired, and others. Thus, there is no comparable data for displaced workers in MPUS, however, the definition of involuntary changers is close to that of displaced workers in some sense.

Table 1 shows the basic properties of the data. The monthly working hours and firm tenure slightly decline over time, while work experience increases gradually and in a relatively stable way. However, the real hourly wages and years of schooling increase significantly. Hourly wages increase from \$56.62 to \$162.04, and years of schooling from 8.09 to 11.42 years. Work experience increases from 13.16 to 15.76.

For the period of 1979–2000, about 8.8 percent of workers change a job each year, among them, 83.4 percent are voluntary and only 16.6 percent are involuntary. Among these job changers, over 67 percent are movers (who switch industry), while 68 percent and 62 percent are in the voluntary and involuntary groups, respectively. That is, workers who change a job tend to switch an industry also, especially for the voluntary changers. Among workers who changed jobs stayers earn more than movers, and 15.5 percent

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[3] In Taiwan, males have to do military service once they reach the age of eighteen and leave school.

were from the group of voluntary changers and 25.89 percent from the group of involuntary changers. However, the average years of schooling remained very stable, and it was 10.5 years for the group of voluntary changers and 9.17 years for the group of involuntary changers.

As for the work experience, workers who change jobs have three years less than the employed workers. However, for those who change jobs, stayers have work experience about one year more than movers for the voluntary group, while movers have work experience roughly 2 years more than stayers for the involuntary groups. Moreover, the involuntary group has work experience about 8 years more than the voluntary group.

4 Estimation Results

As industry switching for job changers is likely a self-selection process, we first estimate the probability of switching an industry. Table 2 shows the results for the first-stage probit model for switching industry of the job changers with explanatory variables including worker characteristics, occupation, work location, firm size, and job growth of the preswitch industry. The results show that workers who are married, have university education, are more experienced, work as administrator or professional, and live in Taipei City do not tend to switch an industry. Moreover, we also find that the preswitch industry's employment share and its growth rate have a positive and significant effect on workers probability to stay at the industry. This is consistent with search theory, i.e., that search cost is usually lower for an industry where it is easier to find a job as the industry expands.

Table 3 shows the results of the wage regressions. Estimation of equation (4) finds that the interaction term of the switching industry dummy (*IND*) and work experience has a positive and significant coefficient, 0.0053 for the voluntary group and 0.0066 for the involuntary group. If we run a wage regression for stayers and movers separately, i.e., equations (2) and (3), with the selection correction term obtained from the first-stage probit model,[4] then we cannot find any significant effect of the correction terms for both groups. This implies that selection may not be significant for the decision

[4] The estimation results remain unchanged under a multinomial logit model for the selection correction among workers who do not change job, who change job but stay in the same industry, and who change job and also switch industry. Estimation results are available upon request to the authors.

Table 2: *Probit Model for Switching Industries (first-stage)*

	Voluntary		Involuntary	
	Coefficients	Standard errors	Coefficients	Standard errors
Constant	−1.4932	0.1223***	−1.8659	0.1916***
Married	0.1313	0.0263***	0.1972	0.0637***
Work location (preswitch)				
Taipei city	0.1420	0.0336***	0.1337	0.0780*
Southern cities	0.0009	0.0372	0.0371	0.0802
North region	0.0559	0.0315*	−0.0490	0.0678
Central region	0.0025	0.0335	−0.1262	0.0732
East region	−0.1039	0.0891	0.1132	0.1532
Firm size (preswitch)				
2 ~ 9 persons	0.6644	0.0613***	1.0686	0.1021***
10 ~ 29 persons	0.7534	0.0620***	1.3414	0.1049***
30 ~ 49 persons	0.7122	0.0668***	1.1154	0.1236***
50 ~ 99 persons	0.6598	0.0680***	1.2142	0.1245***
100 ~ 499 persons	0.6743	0.0653***	1.1250	0.1184***
above 500 persons	0.4764	0.0812***	1.1718	0.1488***
Occupation (preswitch)				
Administrator	0.2190	0.1150**	0.0408	0.2114
Professional	0.1052	0.0456**	0.2264	0.1120**
Clerks	−0.2086	0.0576***	−0.0456	0.1312
Service workers	−0.0012	0.0400	−0.2960	0.1090***
Production and machine operators	0.0266	0.0254	−0.0149	0.0564
Industry's employment share (preswitch)	0.0238	0.0036***	0.0519	0.0075***
Growth of industry's employment share (preswitch)	0.0038	0.0008***	0.0088	0.0019***
Education				
Primary school	−0.0284	0.0948	0.0953	0.1376
Junior school	−0.0468	0.0986	0.1501	0.1497
Senior school	−0.0394	0.1034	0.1012	0.1640
Vocational school	−0.0564	0.1005	0.1149	0.1566
Junior college	0.1276	0.1040	0.4011	0.1742**
University	0.2456	0.1069***	0.4869	0.1828***
Preswitch work experience	0.0212	0.0036***	0.0063	0.0078
(Preswitch work experience)^2	−0.0004	0.000081***	−0.0001	0.0001
Mean of dependent variable (*stay* = 1, *move* = 0)		0.3257		0.3922
Pearson statistics		16,468.5094		3,305.8167
Observations		16,430		3,272

*, **, *** significant at the level of 10, 5, and 1 percent, respectively.
Note: The larger the model coefficients are, the higher the probability of staying in the same industry becomes. Reference groups are: South region for work location; 1 person for firm size; agriculture, forestry, and fishing workers for occupation; and illiterate or self-educated for education. Preswitch work experience does not include current firm tenure.

Table 3: *Estimation Results for Wage Determination (second-stage)*

	Voluntary changers			Involuntary changers		
	Whole samples (no correction)	Divided samples		Whole samples (no correction)	Divided samples	
		Stayers	Movers		Stayers	Movers
Work experience	0.0332	0.0405	0.0321	0.0230	0.0270	0.0250
	(0.0010)***	(0.0020)***	(0.0012)***	(0.0024)***	(0.0037)***	(0.0031)***
IND × (work experience)	0.0053	–	–	0.0066	–	–
	(0.0004)***	–	–	(0.0006)***	–	–
Firm tenure	0.2167	0.1862	0.2214	0.0497	−0.1660	0.1913
	(0.0278)***	(0.0508)***	(0.0332)***	(0.0705)	(0.1117)	(0.0917)**
(Work experience)^2	−0.0007	−0.0008	−0.0007	−0.0006	−0.0006	−0.0006
	(0.000021)***	(0.000042)***	(0.000026)***	(0.000044)***	(0.000070)***	(0.000058)***
(Firm tenure)^2	−0.1020	−0.0964	−0.0995	−0.0184	0.1336	−0.1161
	(0.0202)***	(0.0366)***	(0.0242)***	(0.0524)	(0.0836)	(0.0679)*
Education						
Primary school	−0.0734	0.0270	−0.1300	−0.1269	−0.1076	−0.1425
	(0.0251)***	(0.0448)	(0.0304)***	(0.0389)***	(0.0779)	(0.0459)***
Junior high school	−0.0483	0.0964	−0.1243	−0.1000	−0.1263	−0.1027
	(0.0263)*	(0.0471)**	(0.0318)***	(0.0432)**	(0.0857)	(0.0514)**
Senior high school	0.0554	0.1716	−0.0046	−0.0925	−0.1225	−0.0848
	(0.0276)**	(0.0496)***	(0.0334)	(0.0480)*	(0.0913)	(0.0581)
Vocational school	0.0634	0.1931	−0.0046	−0.0729	−0.1255	−0.0444
	(0.0269)**	(0.0482)***	(0.0325)	(0.0454)	(0.0879)	(0.0545)
Junior college	0.1829	0.2926	0.1266	0.0068	−0.0119	−0.0093
	(0.0283)***	(0.0506)***	(0.0339)***	(0.0524)	(0.0979)	(0.0653)
University	0.4259	0.5516	0.3565	0.1474	0.1672	0.0507
	(0.0291)***	(0.0519)***	(0.0355)***	(0.0564)***	(0.1006)*	(0.0748)
Selection correction term	–	−0.0774	0.0323	–	−0.0454	0.0534
	–	(0.0525)	(0.0330)	–	(0.0622)	(0.0407)
Adj. R^2	0.6296	0.6214	0.6266	0.5618	0.5619	0.5064
Observations	16,430	5,256	11,174	3,272	1,259	2,013

Figures in parentheses are standard errors and *, **, and *** are significant at the level of 10, 5, and 1 percent, respectively.
Note: Besides the above items, all the regressions include an intercept, time dummies, marriage dummies, occupation dummies, work-location dummies, firm-size dummies, and industry's employment share, and its growth rate. IND is a dummy variable: 1 for staying in the same industry, 0 for moving to another industry.

of switching an industry.[5] We find in both cases that the coefficient of work experience for stayers is significantly higher than that for movers, 26.17 percent for the voluntary group and 8 percent for the involuntary group.[6] These results strongly imply that workers who switch an industry do incur a wage loss, mainly because of the existence of industry specific human capital. More interestingly, we find that after this industry-specific human capital is taken into account, the coefficient of firm tenure becomes insignificant in the involuntary group, however, it remains positive and significant for the voluntary group.

As our data is confined to workers with firm tenure less than one and half years, the positive and significant effect of firm tenure is therefore likely to reflect the job-related skill effect as pointed out by Altonji and Shakotko (1987) and Altonji and Williams (1992). Moreover, the larger effect of firm tenure for the movers over the stayers (about 19 percent for the voluntary group) confirms this job-related skill-matching hypothesis. This finding is consistent with Neal (1995) and Parent (2000), whereby firm-specific factors may contribute little to the observed slope of wage tenure profiles. Furthermore, what matters most for the wage profile in terms of human capital is industry specificity, not firm specificity.

The effect of industry-specific human capital may additionally be varied among different educational levels. Table 4 shows the results by including the interaction terms of work experience with the educational dummy for movers and stayers. In general, for both voluntary and involuntary groups, the effect of work experience declines along the educational ladder; the lower the educational level, the greater the effect. The reason of this may be that general training is more important for low-skilled workers than for high-skilled workers, as low-skilled workers usually learn general skills at the workplace, while high-skilled workers normally receive general training from colleges and universities.[7]

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[5] The decision of switching an industry may likely be a random process purely depending on a sheer luck or opportunities that are available under the economic circumstances. Alternatively, it may be due to a problem with the instruments in the estimation. In their study of the possible selective bias for the voluntary switchers, Krueger and Summers (1988) find that selectivity forces are not very important in the longitudinal analysis.

[6] This result is consistent with the finding of Gibbons and Katz (1991) that laid-off workers are, on average, less productive than coworkers who are observationally similar.

[7] A recent study by Weinberg (2002) on the adoption of new technologies also finds a similar result that the use of new technologies increases in experiences for less educated men, but declines in experiences for more educated men.

Table 4: *The Effect of Industry-Specific Human Capital at Different Educational Levels*

	Voluntary changers			Involuntary changers		
	Whole samples (no correction)	Divided samples		Whole samples (no correction)	Divided samples	
		Stayers	Movers		Stayers	Movers
Experience × education						
Illiterate or self-educated	0.0569	0.0598	0.0596	0.0442	0.0381	0.0447
	(0.0037)***	(0.0069)***	(0.0040)***	(0.0067)***	(0.0124)***	(0.0077)***
Primary school	0.0429	0.0423	0.0443	0.0357	0.0348	0.0366
	(0.0016)***	(0.0029)***	(0.0019)***	(0.0038)***	(0.0064)***	(0.0046)***
Junior high school	0.0409	0.0433	0.0418	0.0320	0.0284	0.0325
	(0.0013)***	(0.0024)***	(0.0015)***	(0.0033)***	(0.0051)***	(0.0039)***
Senior high school	0.0329	0.0441	0.0339	0.0251	0.0312	0.0258
	(0.0017)***	(0.0029)***	(0.0018)***	(0.0037)***	(0.0057)***	(0.0042)***
Vocational school	0.0334	0.0410	0.0341	0.0302	0.0325	0.0305
	(0.0013)***	(0.0024)***	(0.0015)***	(0.0032)***	(0.0047)***	(0.0037)***
Junior college	0.0330	0.0391	0.0336	0.0300	0.0287	0.0301
	(0.0018)***	(0.0028)***	(0.0019)***	(0.0046)***	(0.0060)***	(0.0050)***
University	0.0302	0.0420	0.0305	0.0238	0.0265	0.0220
	(0.0020)***	(0.0027)***	(0.0021)***	(0.0050)***	(0.0059)***	(0.0054)***
IND × experience × education						
Illiterate or self-educated	0.0068	–	–	0.0012	–	–
	(0.0061)	–	–	(0.0093)	–	–
Primary school	0.0012	–	–	0.0023	–	–
	(0.0012)	–	–	(0.0025)	–	–
Junior high school	0.0032	–	–	−0.0010	–	–
	(0.0013)**	–	–	(0.0031)	–	–
Senior high school	0.0123	–	–	0.0070	–	–
	(0.0023)***	–	–	(0.0043)	–	–
Vocational school	0.0087	–	–	0.0034	–	–
	(0.0018)***	–	–	(0.0036)	–	–
Junior college	0.0064	–	–	−0.0016	–	–
	(0.0026)**	–	–	(0.0064)	–	–
University	0.0124	–	–	0.0032	–	–
	(0.0026)***	–	–	(0.0061)	–	–
Selection correction term	–	−0.0773	0.0264	–	−0.0502	0.0408
	–	(0.0525)	(0.0328)	–	(0.0626)	(0.0407)
Adj. R^2	0.6331	0.6219	0.6306	0.5663	0.5615	0.5098
Observations	16,430	5,256	11,174	3,272	1,259	2,013

Note: Besides the above items, all the regressions include an intercept, time dummies, marriage dummies, occupation dummies, work-location dummies, firm-size dummies, education dummies, IND × education, firm tenure, (work experience)^2, (firm tenure)^2, and industry's employment share and its growth rate. See also notes in Table 3.

We find that the effect of industry-specific human capital is significant for all educational levels and is particularly stronger for the stayers than for the movers in the voluntary group.[8] This is also confirmed by the regression

[8] We perform the Chow test (1960) to test the equality of the estimated coefficients, i.e., the difference of coefficients of the interaction terms (experience × education) between the voluntary and involuntary groups in Table 4.

of whole sample adding the *IND* dummy variable (1 for stayers and 0 for movers) with the interaction terms, the effect of industry-specific human capital significantly increases along the educational ladder for the voluntary group (see Table 4). The effect for the university level is about 10 times that for primary school and 4 times that for junior high school. These results imply that industry-specific human capital is more important for workers of higher education. For the period 1978–2000 in Taiwan, the percentages of workers who change jobs and switch industry are about 68 percent for high schools, and 63 percent and 50 percent for junior colleges and universities, respectively. These findings are also consistent with many empirical findings showing in general that workers of higher education usually receive more on-the-job training, build up their specific human capital, and therefore tend to stay in the same industry.

5 Concluding Remarks

Using Taiwan's Manpower Utilization Survey data, this paper investigates the effect of industry-specific human capital on wage profile. From the information of last year's job change for junior tenured workers, we infer the effect of industry-specific human capital by comparing the effect of work experience for movers (who switch an industry) and stayers (who do not switch an industry). Other things being equal and holding firm tenure constant, movers actually incur a wage loss measured by the wage premium of the work experience. The larger value of the firm tenure effect versus the average, especially for movers in the voluntary group, reflects an underlying job-related matching process. It is mainly for this gain from a better job match that allows one to overcome the wage loss, and thus stimulates a cross-industry job change. This explains why people who change jobs tend to switch an industry, because the wage gain from a better job match outweighs the wage loss due to a loss of industry-specific human capital.

We also find that the effect of work experience declines with education, while the effect of industry-specific human capital increases with education. This is because low-education workers usually receive their general skill training at the workplace, while the high-education workers gain their general training mainly from colleges or universities. Therefore, we should observe that the effect of work experience declines with education. However, more educated workers usually also receive more on-the-job training than less educated ones. As workers with high education are better equipped to profit from the same on-the-job training, they can better understand the training. Thus, workers who are more educated accumulate more skill-related industry-specific human capital than others. As a result, the effect of industry-specific human capital increases with education. The evidence that the proportion of workers who change jobs and switch an industry declines with education does support that the industry-specific human capital increases with education. The experience of Taiwan's labor market confirms the existence of industry-specific human capital and that rapid voluntary job switching across industries is consistent with the search theory of job matching.

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