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RETURNS TO HUMAN CAPITAL AND WAGE INEQUALITY: THE CASE OF TAIWAN

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To compare with the literature on Taiwan study of wage inequality by the turn of Twenty-First Century, using Taiwan's 1978-2003 Manpower Utilization Survey data, this paper estimates the trends of returns to education and experience and investigates the relationship between returns to human capital, ability, and wage inequality. Over the period, return to higher education has an increasing trend while the wage inequality reveals a declining tendency, a phenomenon also contradicted to existing literature, e.g., Castelló-Climent and Doménech (2014). Using quantile regression, we further discover the relations between human capital accumulation and unobserved ability, i.e., education and ability are substitutes while experience and ability tend to complement each other. Education enables those less able people to improve upon their disadvantages and thus improve wage inequality. Moreover, wage inequality is lower in females than in males for every educational level and more experienced groups. Contrary to the existing literature, Taiwan's empirical study demonstrates that the increasing employment share of more educated workers and/or females will improve instead of worsen wage inequality. Policy implications are also discussed based on Taiwan's experience.

Keywords: Education, Experience, Returns to Human Capital, Wage Inequality
JEL Classification: J24, J31

1. INTRODUCTION

Two recent Taiwan empirical studies reach different conclusions on the effect of return to education and wage inequality. Using Taiwan's Survey of Family Income and Expenditure for the 1978-1996 period, Lin and Orazem (2003, 2004) find that despite the government policy of rapid expansion of a number of higher education institutions since the mid 1980s, the returns to higher education and greater experience are increasing over time, which is mainly due to persistent shifts in relative demand toward skilled labor, i.e. skill-biased technical change. As a result, wage inequality and returns to college-educated workers have risen in Taiwan since 1980. Moreover, the rising share

of women in the labor force helped amplify these trends. The stylized fact is that family income inequality in Taiwan has indeed been increasing since 1980 (as shown in Figure 1 of Lin and Orazem, 2004); however, individual wage inequality has actually been decreasing since 1980 despite the increase in the years of schooling as shown in Figure 1.[1] Chen and Hsu (2001) also document a decreasing trend in wage differentials between skilled and unskilled workers since 1980 and argue that wage inequality has fallen because of decreasing returns to college-educated labor relative to other educational groups.

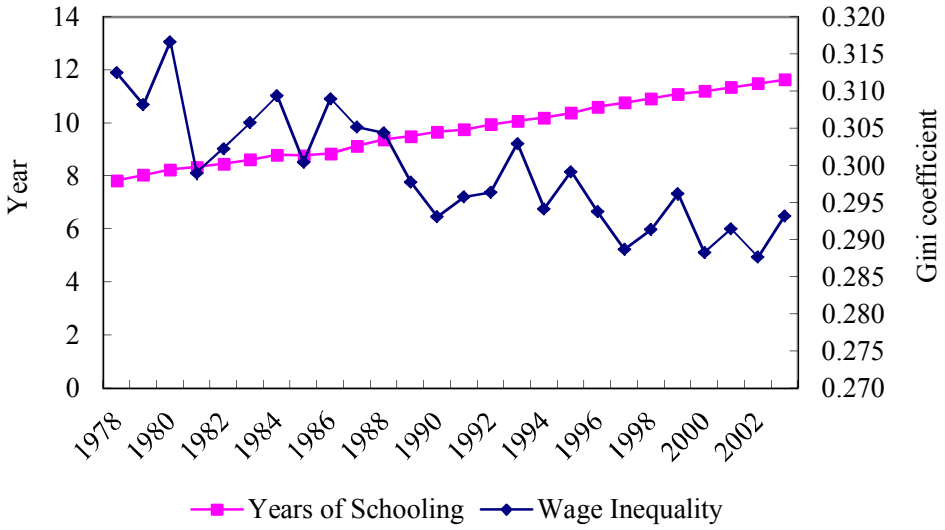

Figure 1. Years of Schooling and Wage Inequality

The returns to human capital seem to play an important role in understanding Taiwan's wage inequality. But, how to reconcile the fact that returns to higher education has an increasing trend while the wage inequality reveals a declining tendency, a phenomenon that contradicted to existing literature?

Empirical studies have shown that rates of returns on human capital are around 15%-20% (see, for example, Heckman, 2003). Cross-country studies have also presented that human capital is a critical factor in enhancing productivity, hence affecting a country's long-run growth (for example, Behanbib and Sprigel, 1994). Human capital

[1] Data for family income inequality in Taiwan can be calculated from the Survey of Family Income and Expenditure, while data for wage inequality can be derived from the Manpower Utilization Survey. Both Surveys are conducted every year by the Directorate-General of Budget, Accounting, and Statistics (DGBAS), Executive Yuan, Taiwan. Using the 1978-2003 Manpower Utilization Survey, Chuang and Lin (2007) also find that inter-industry wage differentials for both males and females have improved over the period.

investment contains the access to new information and knowledge (Thomas et al., 1991) or capability to absorb new information (Schultz, 1975), which in turn enhances productivity. Aside from formal education, which is the major channel for human capital investment, Heckman, Lochner, and Taber (1998) find that about one-third to half of all skill acquisitions are from after school on-the-job training. Education and on-the-job training apparently increase people's productivity and hence the output of the economy. Over time, improvement in labor quality together with economic development also raises workers' wages.

As human capital enhances productivity and hence wages, what is the likely relationship between returns to human capital and wage inequality? Experiences from advanced countries show that human capital investment usually increases the wages of skilled workers and thus widens the wage inequality as the countries develop, see e.g., Kats and Murphy (1992) and Autor, Katz, and Kearney (2008). Pereira and Martins (2000) investigate fifteen European countries during a period ranging between 1980 and 1995, finding that in most countries (except Germany and Greece) the dispersion in earnings increases with educational levels suggesting a positive interaction between schooling and ability with respect to earnings. Hartog, Pereira, and Vieira (2001) examine the evolution of the returns to education in Portugal over the 1980s and early 1990s, also presenting that wage inequality expanded in Portugal over the 1980s and the returns to education had an important role in this process. Saavedra (2001) studies three Latin American countries, Argentina, Brazil, and Costa Rica, and finds that wage differentials arising from education increased in Costa Rica while the relative premium to education fell in Argentina and Brazil. Looking at long-run changes of the U.S. wage structure, Goldin and Kats (2007) conclude that wage inequality was mainly driven by educational wage differentials. A recent study of world data from 1950 to 2010, Castelló-Climent and Doménech (2014) also find that despite the inequality in the distribution of education has been reduced by more than half, inequality in the distribution of income has hardly changed. They claim that the likely reason may be due to the increasing return to education.

Educational investment in Taiwan for the past forty years has shown a remarkable sign of expansion by the turn of the Twenty-First Century. The net enrollment rate of higher education increased from 9.97% in 1976 to 45.68% in 2003. The share of population over age 25 who achieved higher educational attainment increased from 6.63% in 1976 to 24.54% in 2003, a jump of 3.7 times. In the late 1950s to early 1960s, the economic condition in Taiwan was about the same compared to that of other developing countries. However, from then on Taiwan has continuously accumulated its human capital which in turn has contributed to its rapid economic growth. The average annual growth rate of real GDP in 1970-2003 was a strong 7.4%. Chuang (1999) finds that human capital accounts for 46% of output growth in Taiwan's manufacturing industry for the period 1978-94. During the process of rapid economic development, per capita income in Taiwan increased from US$1,758 in 1979 to US$11,710 in 2003, and the average real monthly wage of workers in the industry and service sectors went

from US$420 in 1979 to US$1,234 in 2003. With a rapid growth of income per capita and human capital investment, Taiwan's developmental experience deserves a close examination on returns to human capital and its effect on wage inequality.

The aim of this paper is to disentangle the above-mentioned contradictory conclusion by Chen and Hsu (2001) and Lin and Orazem (2003, 2004) on the returns to human capital and wage inequality in Taiwan by the turn of turn of the Twenty-First Century. Using Quantile regression on Taiwan's data for the period 1978-2003, we intend to identify the relationship between human capital investment and the individual's unobserved ability and offer an explanation why return to higher education has an increasing trend, while the wage inequality shows a declining tendency. A phenomenon also contradicts to existing literature, such as Goldin and Kats (2007) and Castelló-Climent and Doménech (2014). Hence, the results of our finding on Taiwan study may shed important light on policy implications for improving wage inequality through the process of human capital accumulation.

We find that over the period, returns to education has become an increasing trend while returns to experience depicts a declining trend, implying that education of basic knowledge is relatively more important than the training of occupational-specific skills under a dynamic and rapidly changing industrial environment such as in Taiwan. Quantile regression shows that education and ability are substitutes, while experience and ability are complements. Overall, for the whole period, the substitution effect dominates the complementary effect and it contributes to equality wage distribution in Taiwan. Contrary to the existing literature, Taiwan's empirical study demonstrates that the increasing employment share of more educated workers and/or females will improve instead of worsen wage inequality.

This paper is organized as follows. Section 2 describes the empirical model and estimation technique of calculating the returns to education and experience. Section 3 presents the estimation results and discusses the likely implications of human capital investment on wage inequality. Section 4 examines the pattern of Taiwan's wage inequality and verifies the effect of human capital investment on wage distribution within each education, experience, and gender group. A regression analysis of the implications of human capital investment on wage inequality is also tested. Concluding remarks follow in Section 5.

2. THE EMPIRICAL MODEL AND ESTIMATION TECHNIQUE

There are many forms of human capital and it can be accumulated, for example, by education, on-the-job training, health and nutrition, and migration, and so on. In this paper, we mainly consider two of the most important types of human capital accumulation – education and on-the-job training. The standard Mincerian earnings function, introduced by Mincer (1974), is used for the estimation of rates of return to the two types of human capital:

$$LnW_{it} = \alpha_0 + \alpha_{1t}S_{it} + \alpha_{2t}EX_{it} + \alpha_{3t}EX_{it}^2 + \varepsilon_{it}, \quad (1)$$

where the dependent variable is hourly wage in logarithmic form, S is years of schooling, EX is work experience, ε is the disturbance term, and i is an index for worker.

As in Buchinsky (1994), for the purpose of examining the patterns of change in returns to education and experience, the parsimonious specification of equation (1) can be viewed as a reduced-form equation and has the advantage of easy comparability with other studies.[2] The coefficient α_1, a reduced-form coefficient of education, measures gross returns to education which includes all the direct and indirect effects of education on wage. The coefficients $\alpha_2 + 2\alpha_3 EX$ determine the effects of experience on wage and hence are a measure for the returns of on-the-job training. As education has different attainment levels, instead of using years of schooling we also use dummies for different educational attainment levels for estimating the educational wage premium and then use them to calculate the returns to education for various educational attainment levels. In that case, return to education is calculated as the difference of the wage premium between two adjacent education levels divided by the years of higher educational attainment.

As the educational choice is a self-selection process, Chuang and Chao (2001) estimate returns to education using Taiwan's Manpower Utilization Survey data for 1996 by taking into account the relevant selection properties but their results show little bias in conventional estimates. In this paper we do not consider the selection problem; however, the estimation results reported here are comparable to those in Chuang and Chao (2001). Moreover, this paper uses repeated cross-section data and estimates the returns to education and experience for various years by focusing on the identification and comparison of the time pattern for the estimated returns, the selection problem thus is not particularly treated. However, for safety we do adopt Heckman's two-stage method to correct the selection problem for every five years of estimation; the results are also comparable to what we have reported in this paper. The results of relevant selection estimation are shown in Appendix A2. From Figure A1, it is clear that the time trends for return to education at different quantiles are almost the same with or without selection adjustment.

For the research purpose of the paper, we use the quantile regression rather than the traditional Ordinary Least Square (OLS) regression. The OLS regression as in equation (1) gives a grand summary for the averages of the distributions corresponding to the set of X explanatory variables, while the Quantile regression model allows one to estimate the entire conditional distribution of Y given X; see for example, Koenker and Hallock (2001). The quantile regression model can be expressed as

[2] See, for example, Martin and Pereira (2004) for a study of sixteen developed countries.

$$Y_i = X_i'\beta_\theta + u_{\theta i}, \quad \text{with} \quad Quant_\theta\left(\frac{Y_i}{X_i}\right) = X_i'\beta_\theta, \qquad i = 1, \cdots, n, \tag{2}$$

where $Quant_\theta(Y/X)$ denotes the θ conditional quantile of *Y* given *X*. Therefore, the Quantile regression can compute several different regression curves corresponding to the various percentage points of the distributions and thus obtain a more complete picture of the set. In this regard, many empirical studies have used the Quantile regression technique to estimate returns to education and for saving the space we will thus skip the part of standard model specification and estimation; see for example, Buchinsky (1994, 1998), and Mwabu and Schultz (1996), among others for detailed description.

As in equation (1) the major variable left unexplained for wage determination is an individual's unobserved ability. One of the advantages of using the Quantile regression technique to estimate the Mincerian earnings function is that the comparing of human capital returns among different quantiles will enable one to recover the underlying relationship between human capital investment and inherited talent. As there are hidden unobserved abilities in the wage regression, using quantile analysis allows us to infer the individual's unobserved abilities. Other things being equal, when one earns higher income it normally implies that one has higher hidden unobserved ability. If skills and ability are complements as claimed by human capital theory, then, other things being equal, we will expect that the returns to skills at upper quantiles will be higher than those at lower quantiles. As a result, increasing skills usually leads to widening wage inequality under the complementarity hypothesis.[3] In contrast, if skills and ability are substitutes, i.e., those with high ability can earn high income by themselves and are less dependent on accumulating observed skill through, for example, education, then increasing skills will lead to closing wage inequality.

In performing the analysis, one may argue that the rank in the ability distribution may change when the schooling level changes. However, it is rather less likely that high ability people become less ability people as education increases, in particular, when we compare the 10% (or 25%) quantile with the 90% (or 75%) quantile. That is, the one who has high ability above 90% (75%) now becomes the one with ability below the 10% (or 25%) quantile as one receives one more year of education. Therefore, our analysis of comparing a high quantile at 90% (75%) to a low quantile at 10% (25%) should be applicable, and the problem that the ability distribution may change when education changes, if it exists, should not overturn our results.

To be comparable to studies of Chen and Hsu (2001) and Lin and Orazem (2003, 2004), the data used in this paper are from Taiwan's Manpower Utilization Surveys for the period 1978-2003.

[3] See, for example, Hartgo, Pereira, and Vieira (2001) for the interpretation of the results from quantile regression showing that higher returns for workers at higher quantiles likely reflect a complementarity between education and unobserved variables (e.g. ability) to generate wages.

Table 1. Basic Data Analysis

Year	Real Monthly Wage*	Education Years	Experience Years	Distribution of Educational Attainment					Number of Observations
				Primary School	Junior High School	Senior High and Vocational School	Junior College	University	
1978	12810.04	7.55	18.71	0.4600	0.1728	0.1640	0.0412	0.0429	22356
	(10103.56)	(4.04)	(15.48)						
1979	14090.28	7.80	18.59	0.4384	0.1848	0.1763	0.0478	0.0453	23675
	(10382.80)	(4.03)	(15.34)						
1980	14215.22	8.05	19.27	0.4169	0.1918	0.1923	0.0514	0.0496	24417
	(10567.92)	(4.03)	(15.12)						
1981	14955.32	8.16	19.14	0.4117	0.1955	0.2024	0.0493	0.0504	25431
	(9538.41)	(3.98)	(15.01)						
1982	16039.37	8.33	19.25	0.4001	0.1969	0.2129	0.0567	0.0506	25608
	(10055.66)	(3.96)	(14.81)						
1983	16822.52	8.56	19.35	0.3756	0.1942	0.2287	0.0642	0.0572	26244
	(10563.89)	(4.02)	(14.88)						
1984	17280.15	8.69	19.18	0.3629	0.1967	0.2395	0.0661	0.0591	27668
	(11476.06)	(4.00)	(14.89)						
1985	17893.45	8.71	19.31	0.3559	0.2008	0.2407	0.0705	0.0559	27464
	(11069.91)	(3.99)	(14.83)						
1986	18967.16	8.75	19.40	0.3431	0.2093	0.2447	0.0687	0.0567	27784
	(12062.99)	(4.00)	(14.91)						
1987	20080.70	9.02	19.31	0.3269	0.2035	0.2622	0.0800	0.0603	29694
	(12599.46)	(3.96)	(14.82)						
1988	22053.32	9.22	19.44	0.3215	0.2005	0.2767	0.0833	0.0617	29606
	(13819.11)	(3.89)	(14.55)						
1989	24520.97	9.36	19.54	0.3065	0.1988	0.2863	0.0854	0.0685	29243
	(14621.26)	(3.91)	(14.52)						
1990	26440.66	9.50	19.47	0.2947	0.2016	0.2972	0.0895	0.0681	28434
	(15300.27)	(3.84)	(14.44)						
1991	28720.63	9.58	20.09	0.2922	0.2059	0.3002	0.0908	0.0680	27830
	(18826.85)	(3.77)	(14.16)						
1992	30647.52	9.79	20.18	0.2760	0.1996	0.3111	0.1031	0.0721	27743
	(25730.16)	(3.74)	(14.00)						
1993	32323.95	9.81	20.37	0.2696	0.2031	0.3135	0.1025	0.0722	30084
	(29384.89)	(3.75)	(14.17)						
1994	32959.70	9.83	20.08	0.2615	0.2147	0.3126	0.1038	0.0696	30551
	(26324.54)	(3.71)	(14.33)						
1995	33711.47	10.07	20.25	0.2436	0.2040	0.3239	0.1137	0.0793	30575
	(31356.85)	(3.74)	(14.33)						
1996	33469.06	10.33	20.11	0.2267	0.1950	0.3330	0.1274	0.0880	29568
	(25770.40)	(3.70)	(14.08)						
1997	33749.93	10.49	20.10	0.2153	0.1928	0.3358	0.1339	0.0950	29326
	(24406.76)	(3.69)	(14.01)						
1998	34863.91	10.66	20.04	0.1959	0.1937	0.3444	0.1378	0.1016	29902
	(27649.00)	(3.68)	(13.85)						
1999	34599.57	10.74	20.07	0.1872	0.1939	0.3450	0.1445	0.1034	29411
	(28709.76)	(3.67)	(13.91)						
2000	34628.65	10.87	20.04	0.1759	0.1939	0.3427	0.1520	0.1110	29382
	(23202.88)	(3.66)	(13.99)						
2001	34628.65	10.87	20.04	0.1759	0.1939	0.3427	0.1520	0.1110	29382
	(23202.88)	(3.66)	(13.99)						
2002	33207.68	11.21	20.07	0.1524	0.1812	0.3543	0.1606	0.1318	29615
	(21348.79)	(3.58)	(13.65)						
2003	33251.87	11.38	20.21	0.1446	0.1798	0.3511	0.1567	0.1504	28844
	(21684.10)	(3.59)	(13.62)						

Notes: Real wages are calculated using 2001 as the base year. Figures in the parentheses are standard deviation.

Source: Taiwan's Manpower Utilizations Survey.

The MPUS data are repeated cross sections, stratified random samples of nearly 60,000 individuals from around 20,000 households of 7,510 villages and neighborhoods of Taiwan. We consider only full-time employed workers.

Potential work experience is calculated as age – years of schooling – eight for males over 20 (six for females and males under 20).[4] Table 1 shows basic data for regression analysis for the 1978-2003 period. For the past twenty-five years, the real monthly wages in 2001 constant prices increased by about three times starting from NT$12,810 in 1978, reaching a peak of NT$34,684 in 1998, and then remaining relatively stable. Average work experience remained stable at around 20 years. The average years of schooling for employed workers increased from 7.55 years in 1978 to 11.38 years in 2003. For the same period, the share of primary school educational attainment dropped significantly from 46% to 15%, while that of other educational attainments increased; for example, from 16.4% to 35.11% for senior high school and from 4.29% to 15.04% for university. Apparently, over the 1978-2003 period, worker quality in Taiwan significantly improved.

3. ESTIMATION RESULTS OF RETURNS TO HUMAN CAPITAL

Figure 2 shows the rates of return to education and experience from the OLS regression results of equation (1) for various years. The rate of returns to education in Taiwan denotes a stable increasing trend from 5.47% in 1978 to 8.18% in 2003. However, the returns to experience are below 2%, much lower than that of formal education, and show a declining trend starting from 1.76% in 1978 to 1.44 in 2003. Thus, during the 1978-2003 period, returns to education are increasing while returns to experience are declining. Figure 3 presents the rates of return to education regarding various educational levels. In general, returns to education are increasing along the educational ladder with the highest returns of around 12% for the university level. However, the returns to all educational levels except for university show a decreasing time trend before 1995 and then increase afterward. The increasing trend of return to higher education despite of expansion in higher education institutions implies that the demand for skilled workers had largely increased during the period. Using Taiwan's Survey of Family Income and Expenditure for the 1978-1996 period, Lin and Orazem (2003) find that despite the expansion of the number of higher education institutions since the mid 1980s, the returns to higher education and greater experience are increasing over time, which is mainly due to persistent shifts in relative demand toward skilled labor, i.e. skill-biased technical change.

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

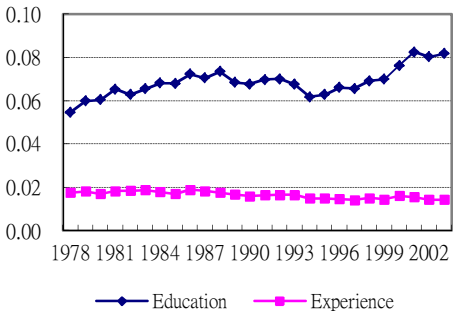

Figure 2. Returns to Education and Experience

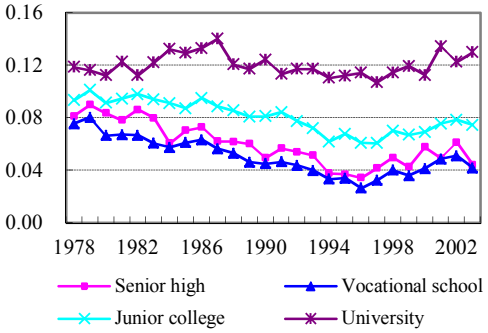

Figure 3. Returns to Education by Education Level

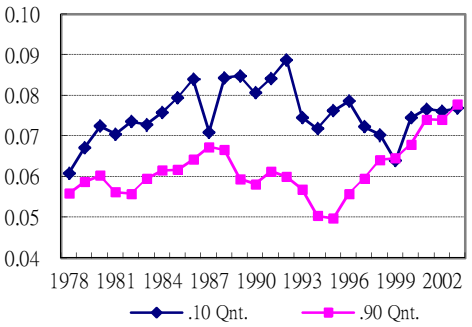

Figure 4a. Returns to Education (.10 and .90 Quantiles)

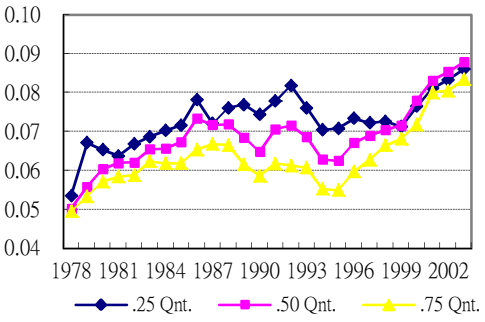

Figure 4b. Returns to Education (.25, .50, and .75 Quantile)

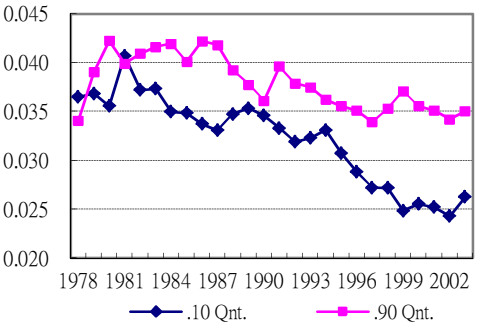

Figure 5a. Returns to Experience: 5 years of experience (.10 and .90 Quantiles)

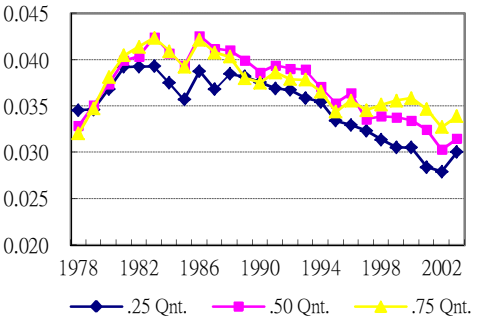

Figure 5b. Returns to Experience: 5 years of experience (.25, .50, and .75 Quantiles)

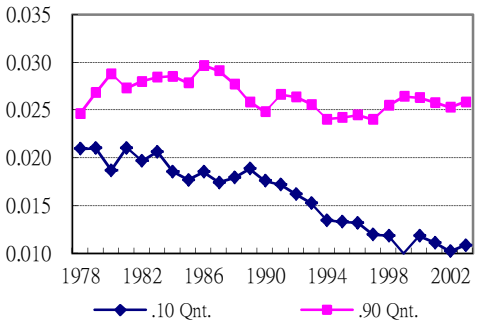

Figure 6a. Returns to Experience: 15 years of experience (.10 and .90 Quantiles)

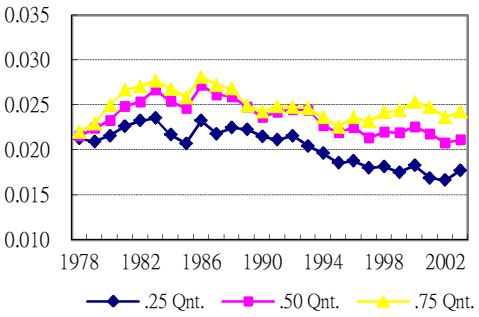

Figure 6b. Returns to Experience: 15 years of experience (.25, .50, and .75 Quantiles)

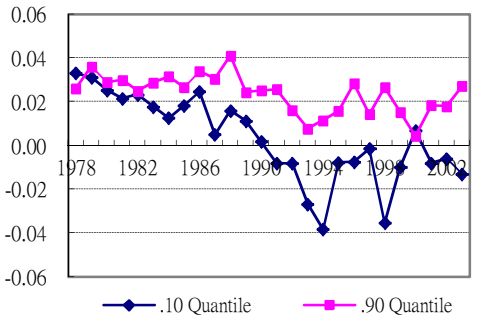

Figure 7a. Returns to Education (Primary School)

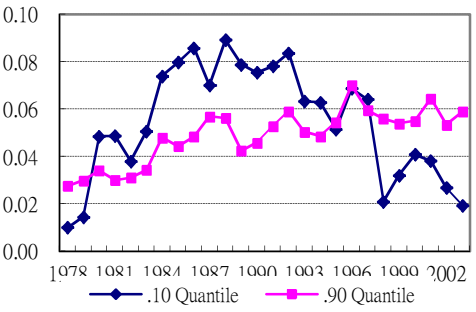

Figure 7b. Returns to Education (Junior High School)

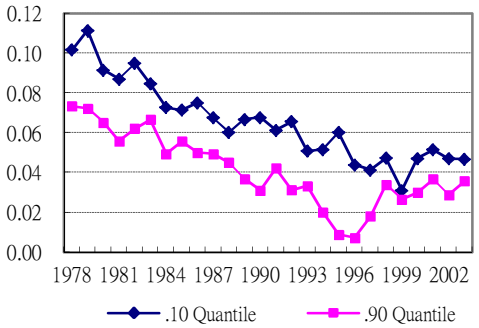

Figure 7c. Returns to Education (Senior High & Vocational School)

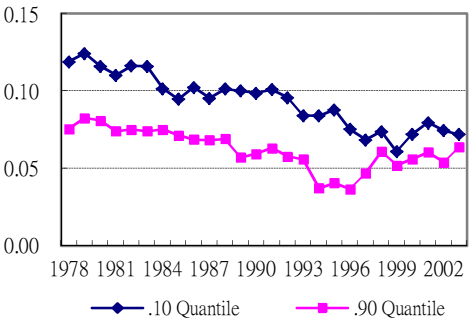

Figure 7d. Returns to Education (Junior College)

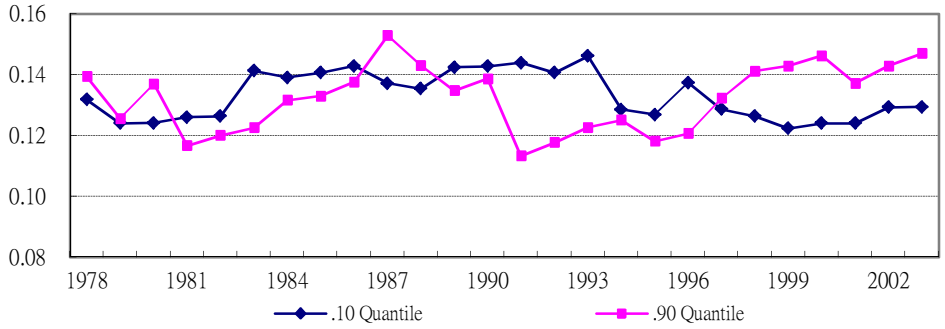

Figure 7e. Returns to Education (University)

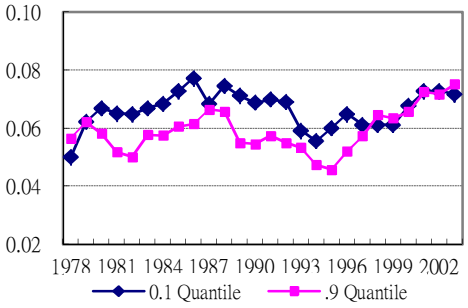

Figure 8a. Returns to Education: Male (.10 and .90 Quantiles)

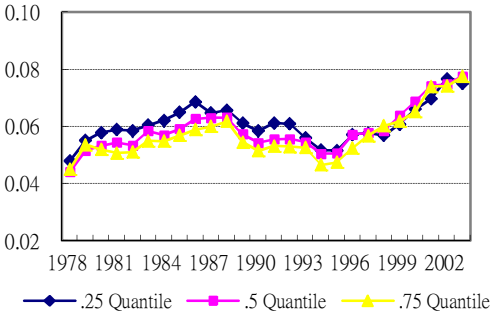

Figure 8b. Returns to Education: Male (.25, .50, and .75 Quantiles)

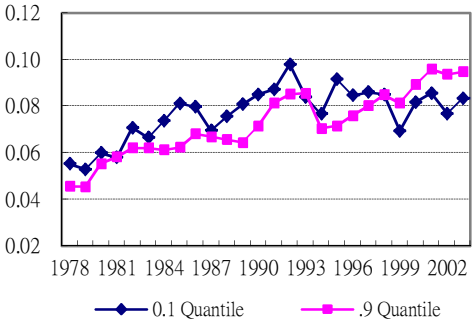

Figure 9a. Returns to Education: Female (.10 and .90 Quantiles)

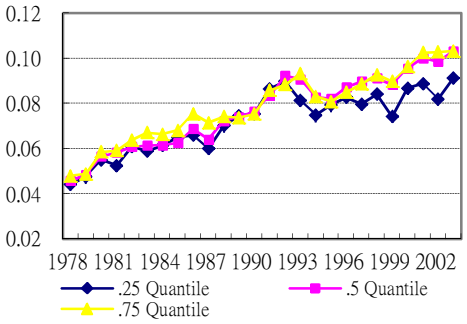

Figure 9b. Returns to Education: Female (.25, .50, and .75 Quantiles)

Using quantile regression, the estimated returns to education and experience at the

five quantiles, .10, .25, .50, .75, and .90, are calculated. Figures 4, 5, and 6 depict the estimated results of returns to education, five years of experience, and 15 years of experience, respectively. On average, the mean rate of return to education is increasing over time and the marginal rate of education is increasing along the educational ladder. Contrary to the findings in Lin and Orazem (2003), the mean rate of return to experience is decreasing over time and that of the five years of experience group is higher than that of the 15 years of experience group, suggesting the experience of young workers is relatively more valuable than that of older workers as the skill content becomes more advanced for younger workers than for older workers and the speed of becoming obsolete is likely faster for old skills than for new skills along the rapid change of industry structure. Thus, the effect of skill-specific training seems to decay over time.

The returns of education and experience at each quantile change in a similar pattern as the mean returns to education and experience; however, the returns at these five quantiles are substantially different. In general, the returns to education are higher at lower quantiles, while the returns to experience are higher at higher quantiles. Moreover, the gap of returns to education between the .10 and .90 quantiles widens over time before 2000 and then it contracts. However, the gap of returns to experience between the .10 and .90 quantiles is widening throughout the whole period, and the gap of return is even larger for the 15-years-of-experience group than for the five-years-of-experience group.

Comparing the returns of different quantiles will enable us to identify the relationship between education (experience) and unobserved ability. The higher the return on a lower (higher) quantile over a higher (lower) quantile implies that the underlying unobserved ability is relatively vigorous and more effective in learning for a lower (higher) quantile than for a higher (lower) quantile. Thus, these results of quantile regressions imply that education and ability are substitutes while experience and ability are complements, and the complementarity increases as the experience accumulates. Our empirical study of Taiwan is in opposition to the argument of the sorting of ability by schooling or signal model for schooling.[5]

We further calculate the returns at each quantile by educational level. The results are shown in Figure 7. For the group with a primary school education, the returns are higher at higher quantiles for the whole period. For the groups with junior high school and university education, the returns are higher at lower quantiles before 1998 and then the returns are higher at higher quantiles afterward. For the groups of senior high and vocational schools and junior colleges, the returns are higher at lower quantiles throughout the whole period. Therefore, except for primary school education, education and ability are substitutes, especially for the groups of senior high and vocational schools and junior colleges, which have the largest deviation of returns between upper and lower quantiles. These results imply that at least before the mid 1990s all the education groups except for primary schools play an important role in the formation of

[5] See, for example, Cawley, Heckman and Vytlacil (1998) and Spence (1973).

skill and capability, and thus education can be an effective tool to substitute for ability, especially for the group of senior high and vocational schools and junior colleges.

The substitutability between education and ability implies that an increase in education will contract wage differentials among workers with higher education. However, the complementarity between experience and ability verifies the process of learning-by-dong. Under above findings, therefore, we end up with Hypotheses 1 and 2.

H1: When education and ability are substitutes, the increasing share of high skilled workers over time will improve wage inequality.

H2: When on-the-job training and ability are complements, wage inequality will be higher among more experienced workers than among less experienced ones.

It has been documented in the literature that the returns to education and experience may be quite different between males and females; see, e.g. O'Neill and Polachek (1993) and Blau and Kahn (1992), among others. We further estimate the returns to education and experience for males and females separately. Figures 8 and 9 show that the returns of education are higher at lower quantiles for both males and females before 1998, and then both the upper and lower quantiles converge for males and the upper quantile surpasses the lower quantile for females. These results imply for both males and females before 1998 that education and ability are substitutes, which will help to reduce the wage inequality among skilled workers in both groups. This gives us Hypothesis 3.

H3. With the substitutability between education and ability, the increase of females in the labor market will attenuate wage inequality as the rate of return to education is higher for females than for males.

Figures 10 and 11 present the results of returns to five years and 15 years of experience for males and females, respectively. For the five-years-of-experience group, the returns to experience for males are higher at lower quantiles before 1998, and then they converge afterward, while those for females are higher at higher quantiles for the whole period. However, for the 15-years-of-experience group, the returns to experience for both males and females are higher at higher quantiles for the whole period, and the differences between upper and lower quantiles are widening over time for males and remain stable for females. These results imply that experience and ability are complements for both male and female groups except for those less experienced males whose experience and ability are substitutes. Moreover, the complementarity effect of experience and ability is larger for older workers than for younger workers for both females and males. Therefore, from the results of quantile estimation we expect that wage inequality should be higher among more experienced workers for both males and females. As for the less experienced male workers, their wage differentials will be smaller than in other groups.

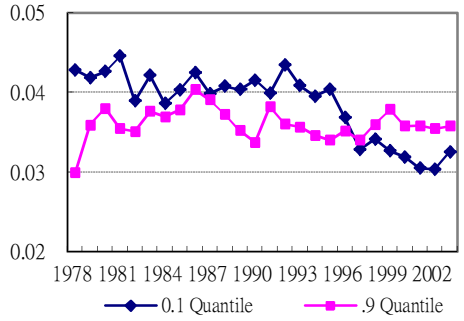

Figure 10a. Returns to Experience: Male (5 years of experience)

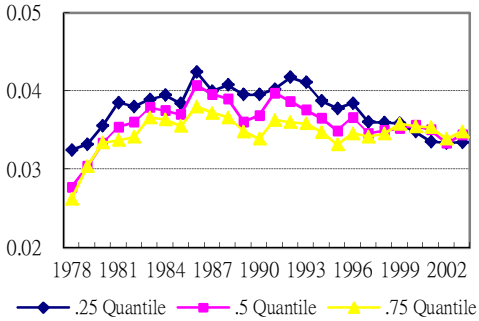

Figure 10b. Returns to Experience: Male (5 years of experience)

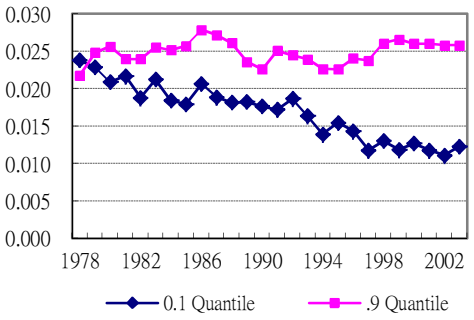

Figure 10c. Returns to Experience: Male (15 years of experience)

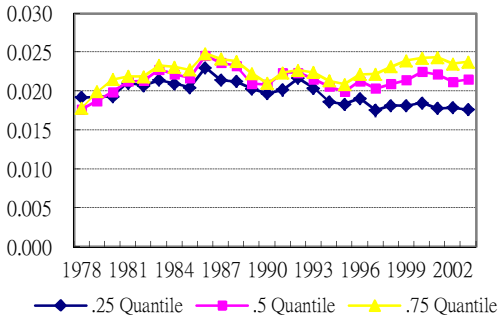

Figure 10d. Returns to Experience: Male (15 years of experience)

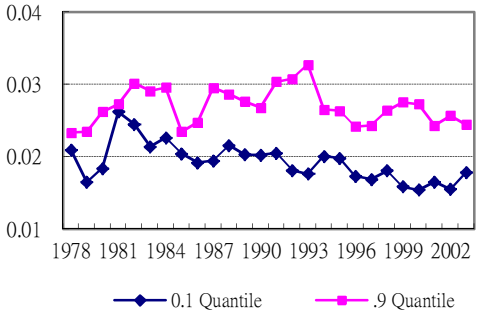

Figure 11a. Returns to Experience: Female (5 years of experience)

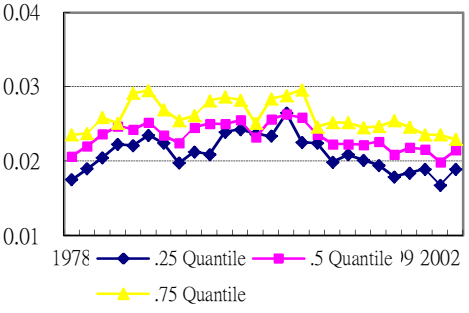

Figure 11b. Returns to Experience: Female (5 years of experience)

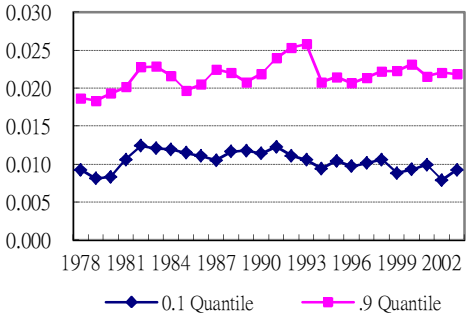

Figure 11c. Returns to Experience: Female (15 years of experience)

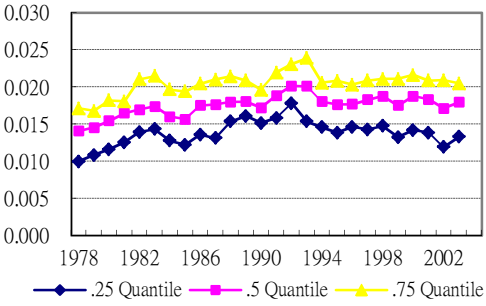

Figure 11d. Returns to Experience: Female (15 years of experience)

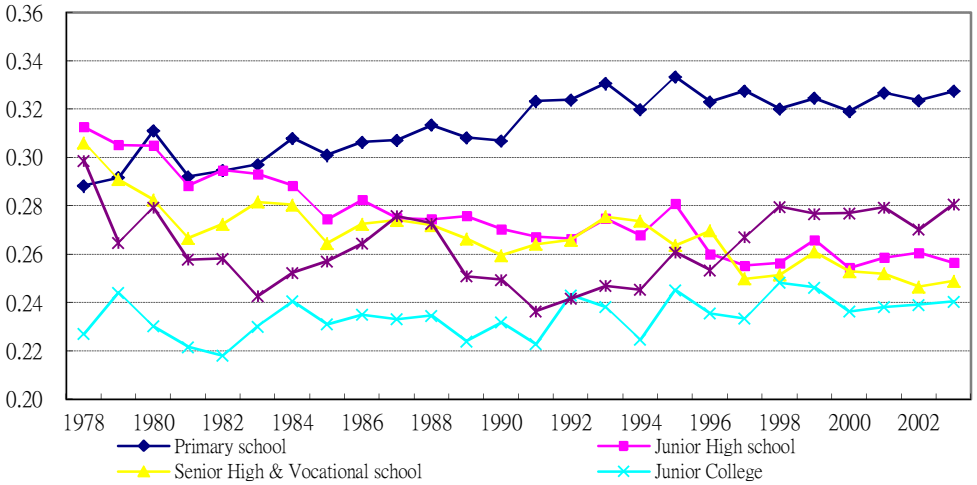

Figure 12. Wage Inequality by Educational Level: Gini Coefficient

4. WAGE INEQUALITY

Based on the findings and hypotheses drawn from previous sections regarding the relationship between human capital accumulation and ability, this section intends to verify the trend of and test the hypotheses for wage inequality. Wage inequality is measured by the Gini coefficient. Figure 12 presents the wage inequality by educational level. Wage inequality is the highest in primary school, followed by junior high and senior high schools and then university, with the lowest in junior college. Primary school shows an increasing trend in wage inequality from 0.29 in 1978 to 0.33 in 2003.

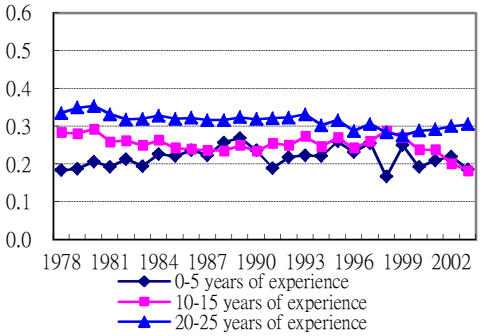

Figure 13a. Wage Inequality by Experience (Primary School)

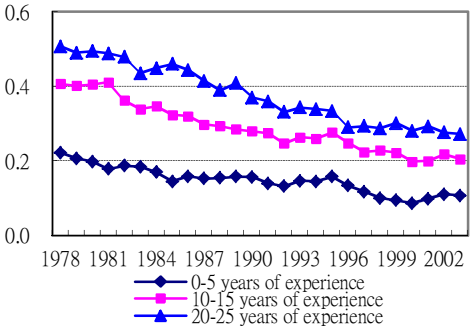

Figure 13b. Wage Inequality by Experience (Junior High School)

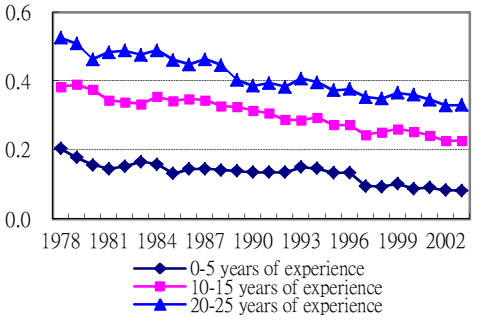

Figure 13c. Wage Inequality by Experience (Senior High & Vocational School)

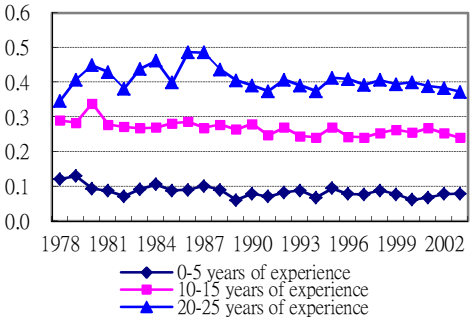

Figure 13d. Wage Inequality by Experience (Junior College)

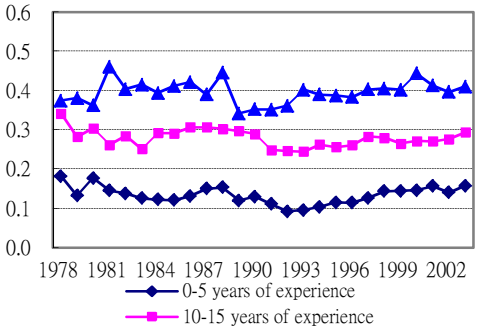

Figure 13e. Wage Inequality by Experience (University)

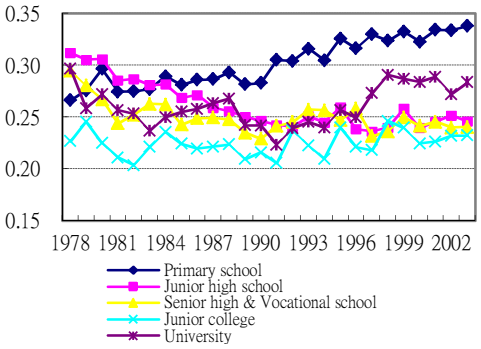

Figure 14a. Wage Inequality by Educational Level (Male)

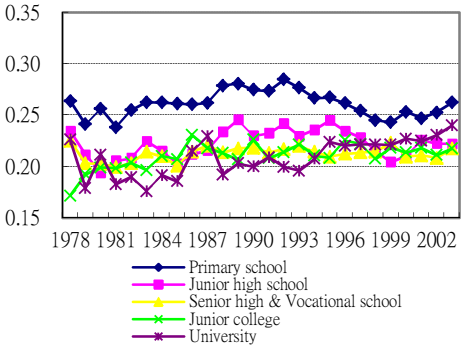

Figure 14b. Wage Inequality by Educational Level (Female)

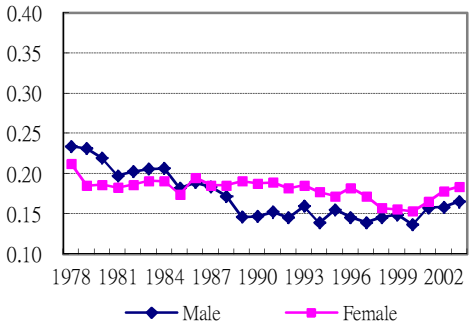

Figure 15a. Wage Inequality by Gender (0-5 years of experience)

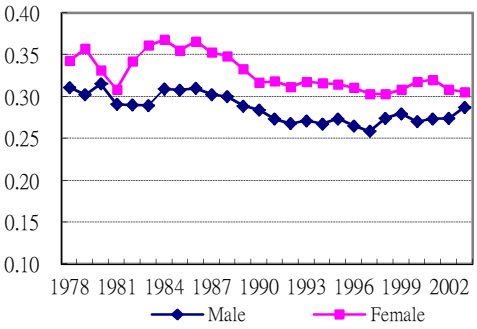

Figure 15b. Wage Inequality by Gender (10-15 years of experience)

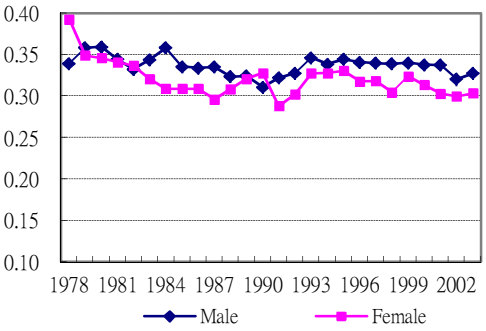

Figure 15c. Wage Inequality by Gender (20-25 years of experience)

However, junior high schools, senior high schools and vocational schools have a declining trend in wage inequality. Junior college shows a moderate increasing trend in wage inequality and the university level remains relatively constant over the whole period with a decreasing trend in the 1980s and an increasing trend in the 1990s. The substitutability between education and ability and the shortening gap between returns of the upper and lower quantiles support the decreasing trend or moderate increase of wage inequality for most education levels except primary school. However, the complementarity between primary education and ability and the widening gap between returns of the upper and lower quantiles support the increasing trend of wage inequality for primary education. Thus, the prominent declining trend of junior high school and senior high and vocational schools contributed to the overall drop in wage inequality as a whole since those groups occupy the largest employment share in Taiwan's labor market.

Figure 13 shows the wage inequality of less than five years, 10-15 years, and 20-25 years of experience by educational level, respectively. In all educational levels, wage inequality is always higher at a higher experience level. This evidence is justified by the finding of complementarity between experience and ability. Moreover, a significant declining trend of wage inequality among different experience levels, especially the more experienced level, is found for junior high school and senior high and vocational schools. This is likely due to the strong substitutability between education and ability that dominates the weak complementarity between experience and ability as the rate of return is higher for education than for experience.

Figure 14 shows the wage inequality by educational level for males and females. Female wage inequality is also larger for a lower educational level. However, in every educational level the female wage inequality is always smaller than the male's but showing a relatively stable trend. The smaller wage inequality for females than for males is mainly due to a large proportion of females tending to work in the service sector and a greater proportion of males usually working in the manufacturing industry. The wage gap is typically lower in the service sector than in manufacturing.[6] Therefore, the increasing share of female workers in the labor market will tend to reduce wage inequality in Taiwan rather than deteriorate the wage inequality as claimed by Lin and Orazem (2004).

Figure 15 presents the wage inequality by gender for 0-5 years, 10-15 years, and 20-25 years of experience, respectively. The wage inequality remains relatively similar and stable over time for both males and females, and wage inequality is higher among more experienced groups. In particular, female wage inequality is slightly larger than that for males in the groups of 0-5 years and 10-15 years of experience and somewhat smaller than that for males in the group of 20-25 years of experience, again contrary to Lin and Orazem's (2004) argument that wage inequality is relatively higher for older

[6] By analyzing inter-industry wage gaps in Taiwan, Chuang and Lin (2007) find that the wage gap in the service sectors such as in the financial services is much lower than that in manufacturing.

college-graduate female workers. These results are consistent with the finding that experience and ability are complements, and the complementarity effect is larger for males than for females.

Therefore, an investigation of wage inequality by gender, education, and experience grouping confirms the relationship between skills and ability found by the quantile regressions. As proposed in Hypotheses 1, 2, and 3, we expect that the increasing employment share of more educated workers or female workers in the labor market will improve the measure of wage inequality, while the increasing share of more experienced workers will deteriorate wage inequality in Taiwan. A regression on wage inequality tests for these hypotheses. Thus, the empirical model for wage inequality regression is specified as

$$WIEQ = \alpha_0 + \beta_1 + \frac{N_w}{N} + \beta_2 \frac{N_{20}}{N} + \beta_3 \frac{N_{cu}}{N_p} + \varepsilon, \quad (3)$$

where $WIEQ$ is for wage inequality measured by the Gini coefficient of wage rate; N_w, is the number of female workers, N_{20} is the number of workers with more than 20 years of experience, N_{cu}, is the number of workers with college or university education, N_p are the number of workers with primary education, N is the total number of workers, and ε is the error term. The three explanatory variables in equation (3) represent the employment share of female workers, the employment share of experienced workers, and the relative employment share of more educated to less educated workers. We expect coefficients β_1 and β_3 to be negative and β_2 to be positive.

Regression results for wage inequality are shown in Table 2. Consistent with our hypotheses, we find increasing employment share of workers with college or university education significantly reduces wage inequality, while increasing employment share of more experienced workers significantly increases wage inequality. The coefficient for the share of female workers as expected is negative but insignificant. This is mainly due to a high correlation of the employment share of female workers with employment shares of workers with college or university education; the corresponding correlation coefficients are 0.8992 and 0.8718, respectively. It is because female with higher education is more likely to enter the labor market and more importantly female labor participation is an endogenous decision process. Likewise, we adopt the instrumental variable method to solve the problem of endogeniety for female employment share. The two instrumental variables for the employment share of female workers are the number of female workers that are the major income source of a family to the total number of workers that are the major income source of a family and the employment share of fashion models, customer sales representatives, and exhibition salespersons, occupations mostly employed with female workers.

Table 2. Regression Results for Wage Inequality

	OLS		IV	
	(1)	(2)	(3)	(4)
N_f/N	-0.0834	-0.0113	-0.1563*	-0.1625*
	(0.0931)	(0.0887)	(0.0805)	(0.0832)
N_{20}/N	0.2343***	0.2256**	0.2422***	0.2321***
	(0.0817)	(0.0898)	(0.0733)	(0.0881)
N_c/N_p	-0.0666***		-0.0341**	
	(0.0175)		(0.0165)	
N_u/N_p		-0.0728***		-0.0387**
		(0.0228)		(0.0192)
Constant	0.1860***	0.2118***	0.2873***	0.2944***
	(0.0540)	(0.0558)	(0.0496)	(0.0512)
Instrument relevance test				
F-test			113.65***	113.65***
Instrument exogeneity test				
Over-identifying restrictions test			5.22	4.35
Adj-R^2	0.6961	0.6549	0.7072	0.7017

Notes: Standard errors are in parentheses. ***, **, and * represent statistical significance at 1%, 5%, and 10%, respectively. N_c and N_u represent the number of workers with college and university education, respectively. Instrumental variables for the employment share of female workers is the number of female workers who are the main income source of the family to total number of workers who are the main income source of the family and the employment share of model, sales service workers, and exhibition sales instructors. The null hypothesis of the F-test is that the instruments have no explanatory power. The null hypothesis of over-identifying restrictions test is that all the instruments are exogenous.

Econometrically, in the 2SLS estimation, a valid instrumental variable should satisfy two conditions: Instrument relevance and Instrument exogeneity.[7] The relevant tests include using the partial coefficient of determination or F-test to test the explanatory power and sign of the instrumental variable on the endogenous variable at the first step of regression.[8] As for the exogeneity test, the over-identifying restrictions test is used on the orthogonality condition for all the instruments.[9] In the second stage of regression,

[7] See, for example, Stock and Watson (2007).

[8] See Bound, Jaeger, and Baker (1995) and Staiger and Stock (1997) for detailed descriptions of the relevant tests. The F-test can be used to joint test the significance of coefficients of all the instrumental variables. A rule of thumb is that F statistics should be greater than 10, and that any values below 10 imply that the selected instrumental variables have insignificant explanatory power or a weak instrument and thus generate estimation bias.

[9] Assume that the number of selected instruments is m and the number of relevant endogenous variables is k. If $m = k$, the regression coefficients are exactly identified. If $m > k$, the regression coefficients are over-identified. If $m < k$, the regression coefficients are under-identified.

we adopt the Durbin-Wu-Hausman test for exogeneity.[10]

Using the F-test for the explanatory power of the instrumental variables and over-identifying restrictions test for instrument exogeneity, our two instrumental variables satisfy both relevance and exogeneity conditions. By the instrumental variable method, we find that the estimated coefficient of the employment share of female workers turns out to be negative and significant, which justifies our hypothesis that the increasing share of females in the labor market will improve instead of deteriorate wage inequality.

5. CONCLUDING REMARKS

To compare with the literature on Taiwan study of wage inequality by the turn of Twenty-First Century, using Taiwan's 1978-2003 Manpower Utilization Survey data, this paper first estimates the trends of returns to education and experience. The mean return to education in general is about 6.5% higher than that of 1.7% of experience. However, over the period, the returns to education have an increasing trend while returns to experience depict a declining trend; this implies that the education of fundamental knowledge is relatively more important than experience or training in specific skills under a dynamic and rapidly changing industrial structure and open environment such as in Taiwan.[11]

We then conduct Quantile regression analysis. Quantile regressions on the conditional distribution show that in general, different quantiles have the same pattern as mean value. However, returns to education are higher for lower quantiles than higher quantiles, meaning that education and ability are substitutes, while returns to experience are higher in higher quantiles than in lower quantiles, showing that experience and ability are complements. The substitutability between education and ability shrinks wage inequality, while the complementarity between experience and ability widens wage inequality. However, over time as returns to education increased and that of experience declined, the substitution effect dominates the complementarity effect and results in improving wage inequality in Taiwan for the entire period! We also find that wage inequality declines along the educational ladder and increases with the level of experience. Moreover, wage inequality is lower in females than in males. As a result, the increasing employment share of more educated workers and/or females in the labor

[10] The estimation process is similar to test for the omitted variable, as it was first proposed by Durbin (1954), Wu (1973), and Hausman (1978), respectively; hence it is also called the Durbin-Wu-Hausman (DWH) test. For a discussion of DWH test of exogeneity, see, for example, Davidson and MacKinnon (2003).

[11] Hamermesh (2005) points out that the general course may be more important than the vocational one as it can increase students' mental flexibility and demonstrate its capability of dealing with new situations. See also Berman, Bound, and Machine (1998) for evidence of technology-skill complementarity.

market will improve instead of deteriorate wage inequality as claimed by Lin and Orazem (2003, 2004) or recent study on a large set of countries by Castello-Climent and Doménech (2014) . A regression analysis on aggregate wage inequality also confirms these implications from quantile regressions for each education, experience, and gender group. The increasing employment share of more educated workers and/or females in the labor market will improve wage inequality, while the increasing share of more experienced workers will deteriorate wage inequality in Taiwan.

Unlike most findings in the literature whereby education and ability are complements and thus increasing returns to skills tends to widen the wage gap, Taiwan's experience shows that education can be a substitute for ability, so people with lower ability can actually improve themselves through investment in education so as to compensate for their disadvantages in ability, especially at the vocational school and junior college education levels. These results also support the policy of education subsidies and less progressive income tax for income redistribution. In fact, education, especially higher education, in Taiwan is highly subsidized by the government. Tuition for higher education is almost the lowest in East Asia.[12] Hence, low tuition fee allows low ability person to gain access to higher education and at the meantime it reduces wage inequality.

Aside from education subsidies program, education system may also work effectively in another way. The increasing share of students enrolled in vocational and junior college between the 1970s and 1980s helped to stabilize wage distribution in Taiwan. In Taiwan's dual-track educational system, for those junior high graduates who cannot pass the examination to enter a senior high school, which is the major channel to enter a university, their second best choice is to choose either a three-year vocational school or five-year junior college for further accumulation of specific skills. Those people in vocational schools or junior colleges are in general not as smart (or intellectually inclined) as those attending senior high school, but the education at vocational schools and junior colleges provides an alternative for youths to learn specific skills and thus compensate for their relative disadvantage in ability. Therefore, a vocational school and junior college education under the dual-track educational system not only gives less able persons or those less intellectually inclined an opportunity to gain specific-skill knowledge but also an opportunity to enter the university later. This institutional design thus improves wage inequality that might likely be generated by investing in higher education.[13]

[12] For the academic year 2003-2004, the tuition fee of public university in US dollar was $1,790 in Taiwan (14.1% of income), $4820 in Japan (15.5% of income), $1970 in S. Korea (14.76%), $5110 in Hong Kong (22.29% of income), and $11,320 in Singapore (53.49% of income).

[13] A similar implication can also be found in an advanced country such as Germany whose educational system has a special track for vocational education. From various empirical studies, Ammermuller and Weber (2003) conclude that the German wage distribution was relatively compressed and stable over the last 20 years compared to other major economies.

APPENDIX

Table A1. Definition and Summary Statistics for Wage Regression Data

Variable	Definition	Mean	S.D.
$GINI$	Gini coefficient of workers' wage in Taiwan from 1978-2003.	0.2994	0.0078
N_w/N	Ratio of the number of female employed workers to the number of total employed workers. (foreign workers not included)	0.3334	0.0246
N_{20}/N	Ratio of the number of employed workers with 20 years of experience or above to the number of total employed workers. (foreign workers not included)	0.4312	0.0146
N_c/N_p	Ratio of the number of employed workers with a college degree and the number of employed workers with a primary education. (foreign workers not included)	0.1743	0.1118
N_u/N_p	Ratio of the number of employed workers with a university degree or above to the number of employed workers with a primary education. (foreign workers not included)	0.2202	0.1442

Source: The Manpower Utilization Survey in Taiwan, 1978-2003

A.1. Heckman Selection Correction

As labor participation is a self-selection process, to avoid selection bias Heckman's (1979) two-stage selection is further considered. For quantile regression, following Buchinsky (1998) we adopt the Heckman selection correction approach for every five years since 1985. We first estimate the labor participation decision and calculate the inverse Mill's ratio, and then put the inverse Mill's ratio and its square term into the second stage wage regression. We then compare the results of rate of returns to education with and without selection correction.

In the first stage labor participation equation, explanation variables include personal and family characteristics such as age, education, marital status, children, and residential area. The results of labor participation decision using the Probit model for males and females are shown in Tables A2 and A3, respectively.

The results show that for both males and females the greater the age the less the probability of entering the labor market and the higher the education the more likely the success of finding a job. As for marriage, its effect is positive for males and negative for females as males are usually the family head and bear the responsibility of earning money to support the family and females tend to stay at home to take care of the family. However, after the mid 1990s the marriage effect on females turned positive implying that as the economy developed and wages increased the opportunity cost to stay at home increased and thus encouraged females to enter the labor market. Having children will also deter females from entering the labor market. Living in a city implies more job opportunities and thus increases male and female labor participation.

Table A2. First Stage Estimation of Labor Participation Decision (Males)

	1980	1985	1990	1995	2000
Age	-0.0230***	-0.0283***	-0.0316***	-0.0363***	-0.0341***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0007)
Primary education	0.7264***	0.6602***	0.5955***	0.4453***	0.6035***
	(0.0328)	(0.0326)	(0.0367)	(0.0386)	(0.0400)
Secondary education	0.2593***	0.3133***	0.2938***	0.4681***	0.7501***
	(0.0361)	(0.0354)	(0.0393)	(0.0408)	(0.0417)
College and above	0.2646***	0.3853***	0.4028***	0.5024***	0.8591***
	(0.0406)	(0.0390)	(0.0416)	(0.0430)	(0.0432)
Marital status	1.4143***	1.5347***	1.6774***	1.6847***	1.6009***
	(0.0267)	(0.0245)	(0.0242)	(0.0249)	(0.0245)
City	0.1782***	0.1921***	0.2185***	0.2299***	0.2874***
	(0.0196)	(0.0219)	(0.0201)	(0.0244)	(0.0175)
Constant	0.2326***	0.2633***	0.2072***	0.4331***	0.2647***
	(0.0469)	(0.0457)	(0.0503)	(0.0511)	(0.0521)
Pseudo R^2	0.1587	0.1660	0.1763	0.1717	0.1585
Samples	24,111	27,244	29,361	29,769	30,202

Table A3. First Stage Estimation of Labor Participation Decision (Females)

	1980	1985	1990	1995	2000
Age	-0.0146***	-0.0159***	-0.0137***	-0.0140***	-0.0132***
	(0.0011)	(0.0010)	(0.0009)	(0.0009	(0.0009)
Primary education	0.2391***	0.2778***	0.3607***	0.4687***	0.5737***
	(0.0286)	(0.0277)	(0.0308)	(0.0315)	(0.0349)
Secondary education	0.0984***	0.2781***	0.5302***	0.6975***	0.9069***
	(0.0339)	(0.0324)	(0.0354)	(0.0357)	(0.0381)
College and above	0.3310***	0.6630***	0.8501***	1.1610***	1.4069***
	(0.0429)	(0.0396)	(0.0405)	(0.0393)	(0.0407)
Marital status	-0.4128***	-0.1040***	0.0308	0.2706***	0.2974***
	(0.0336)	(0.0303)	(0.0283)	(0.0274)	(0.0277)
Children	-0.4027***	-0.2924***	-0.2803***	-0.3664***	-0.2129***
	(0.0295)	(0.0266)	(0.0266)	(0.0263)	(0.0276)
City	-0.0173	0.0122	0.0271	0.0422***	0.0684***
	(0.0123)	(0.0098)	(0.0191)	0.0153)	(0.0221)
Constant	0.1909***	-0.0139	-0.2855***	-0.5728***	-0.8572***
	(0.0465)	(0.0458)	(0.0502)	(0.0505)	(0.0536)
Pseudo R^2	0.0929	0.0674	0.0636	0.0728	0.0998
Samples	24,053	26,958	27,306	29,344	29,168

Tables A4 and A5 show the results of quantile regression for second stage wage determination with and without selection correction. The estimated rate of return to education with or without selection correction is within a minimum range of between 0.007-0.015. More importantly, the time trend for the return to education is almost the same without or with selection correction under quantile regression as shown in Figures A1.

Table A4. Results of Return to Education: with Selection Correction

	1980	1985	1990	1995	2000
.10 Qnt.	0.0581	0.0662	0.0656	0.0625	0.0614
.25 Qnt.	0.0542	0.0610	0.0623	0.0587	0.0648
.50 Qnt.	0.0512	0.0567	0.0608	0.0525	0.0664
.75 Qnt.	0.0483	0.0534	0.0509	0.0467	0.0645
.90 Qnt.	0.0495	0.0512	0.0484	0.0427	0.0566

Table A5. Results of Return to Education: Without Selection Correction

	1980	1985	1990	1995	2000
.10 Qnt.	0.0714	0.0794	0.0806	0.0762	0.0754
.25 Qnt.	0.0653	0.0717	0.0744	0.0708	0.0765
.50 Qnt.	0.0604	0.0674	0.0648	0.0625	0.0781
.75 Qnt.	0.0571	0.0619	0.0587	0.0550	0.0718
.90 Qnt.	0.0604	0.0618	0.0582	0.0498	0.0680

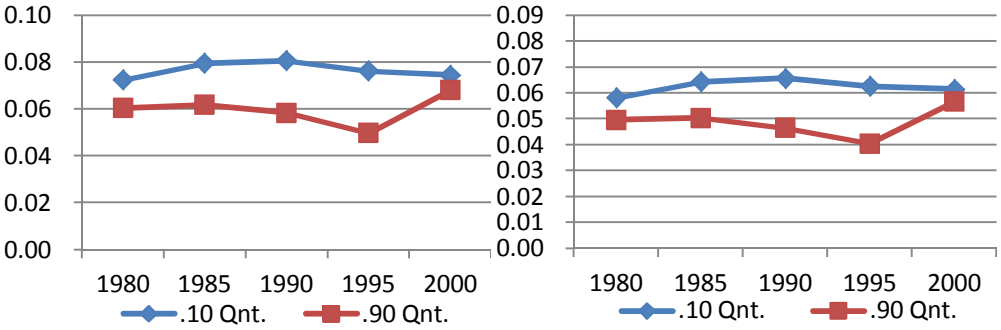

Figure A1. Time Trend of Return to Education: Without and With Selection

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