A Dime for Your Time: Distribution of Earnings in the Malaysian Manufacturing Sector

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Abstract

This paper examines changes in the distributions of earnings of employees in the Malaysian manufacturing sector, using the Malaysian Employee Survey data from the World Bank with a sample size of slightly more than 10,000 respondents. Conventional OLS estimations answer questions such as ‘Does years of education affect salary?’ Quantile estimations however, address questions such as ‘does years of education affect salary differently for those at the upper end of the salary distribution (the relative winners) than for those at its lower end (the relative losers) and the middle-income workers (the averages)?’, where the effects of years of education on a particular earning quantile (or group) can be compared to those on other salary quantiles. Heterogeneity across different salary quantiles can therefore be studied.

Keywords: Salary distribution, Malaysian manufacturing sector, quantile estimation
The use of quantile estimations is also justified if there is evidence of outliers in the dataset. We check for this using a heteroscedasticity test on the explanatory variables. The test reveals a test statistic of 715.06 with a p-value of less than 1%. Therefore, the $H_0$ of homoscedasticity is rejected, suggesting presence of heteroscedasticity (even after we have excluded 1% of the total number of respondents with salaries more than RM7,000). These two quick checks therefore justify the use of quantile estimations in this paper.

4. Discussion of findings & conclusion

Table 1 reports the mean for continuous variables and the mode for categorical variables. The 'All' column reports the means and modes for the entire sample, while the remaining Q1 to Q4 columns report the mean and modes for respondents in the relevant quantile of the salary distribution. We notice that the average salary computed from the entire sample distorts the actual scenario of the salary distribution. There is actually a nontrivial large difference in average salary between employees at the lowest quantile (Q1; a monthly salary of RM552) with those at the highest quantile (Q4; a monthly salary of RM2,795) of the salary distribution. Statistics for the remaining variables can be similarly interpreted.

The OLS estimates in Table 2 show that the mean relationship between the two variables of interest with salary is statistically significant. The effects of these two variables of interest however, tell a different story when we look across the salary distribution, i.e. as shown by the quantile estimates. Using the OLS estimates would have underestimated the effects of these two variables on salary for those at the upper end of the salary distribution, and overestimated the effects for those at the bottom 10% of the salary distribution. Comparing between employees at the top and bottom 10% of the salary distribution, an additional year of education results in almost twice the monthly salary for the top salary earners compared to their counterparts at the bottom 10%. Similarly, an additional year of work experience results in a four-fold (i.e. 38.4 / 9.6) higher salary for the top salary earners. The quantile
variable. Each of the plot also superimposes the quantile estimates on the constant OLS estimates (i.e. do not vary across quantiles), along with their confidence intervals. Figure 2 reveals some other important information which are unavailable from Table 2. Let us look closer at one of our variables of interests – years of work experience – from Table 2. We can see that the quantile estimates for this variable are significantly different from that of its OLS estimate; we know that they are significantly different because the confidence interval for these quantile estimates lie entirely outside of the OLS confidence interval, with the exception of those between quantile 0.6 and 0.8. It is obvious from this result that years of work experience have much less impact on the monthly salary of employees at the lower salary quantiles (approximately below quantile 0.6) compared with their counterparts at the higher salary quantiles (approximately above quantile 0.8). As for our second variable of interest – years of education – Table 2 reveals that there is in fact no significant difference between the quantile and OLS estimates because the OLS estimates’ confidence interval has already subsumed entirely the quantile estimates’ confidence interval. So, in effect, there is no statistical evidence to say that years of education would give different impact on the monthly salary of employees at the higher or lower salary quantiles. These two points would be the main conclusion from this exploratory paper.

In a future extended version of this paper, it will first look at the percentage increase in monthly salary using quantile estimation on a double log model. Secondly, a treatment quantile effect model will be used to address possible biasedness issue resulting from endogenous explanatory variables. As a qualifier, this second extension is only doable if there are good instruments, and these are not easy to come by.

References

