ANALYZING INCOME GAP BETWEEN MIGRANT AND LOCAL WORKERS

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To study gap in income between groups of worker has thus far attracted many economic researchers. In this paper, the dataset to be collated from 401 migrant and local workers will be analyzed to define primary factors affecting such gap and changes in income. Additionally, Mincer's equations, Oaxaca-Blinder decomposition technique, and the quantile regression model by Koenker and Bassett are utilized to facilitate the analysis. The findings show that years of schooling and working experience play an important role in improving income in general; income gap can be explained by gap in years of schooling, working experience, and gender; and such gap show an upward tendency under the impacts of glass ceiling.

Keyword: labor, income estimates, income gap, human capital

1. Introduction

Market discrimination has been a matter of concern to labor economists such as Blinder (1973); Christofides, Polycarpou and Vrachimis (2010), Fang and Sakellariou (2011); Oaxaca (1973); and Reimer (1983). Impacts of gender, ethnicity, occupation, etc. on income gap have been taken into account with the support of various methods. For instance, Oaxaca (1973) and Blender (1973) analyzed income gap between migrant workers and local ones based on human capital, individual characteristics and market discrimination. Recently, Borjas (2010), in his *Labor Economics*, has also mentioned the market discrimination which includes discrimination from employers and local workers against migrant workers.

Overall, recent researches (such as those by Hundel [2000]; Kapsos [2008]; Christofides, Polycarpou and Vrachimis [2010], and Fang and Sakellariou [2011]) often utilize the Oaxaca-Blender decomposition technique to analyze income gap on the basis of gender and occupation. In Vietnam, this issue has recently been discovered from other angles. Walle and Gunewardena (2001), based on the 1993 stat, analyzed gap in living standards of the Kinh and other ethnic groups in Vietnam, and household spending was treated as an important indicator. They found that such gap were attached to socioeconomic conditions, geographical locations, traffic network, and ability to access labor market and non-agricultural jobs.

Gallup (2002) utilized the 1993 and 1998 surveys to estimate income gap between regions on the basis of gender. As the author put it, the marginal earnings from education inched from 2% in 1993 up to 4% or 5% in 1998. More importantly, there seemed to be an income discrimination against female workers concerning their educational level and working experience.

Flows of migrant workers to economic hubs have become a popular social phenomenon since the economic reform in Vietnam. Numerous evidences

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prove that labor migration is connected with push factors in the hometown (i.e. lack of jobs, low income, urbanization, climate change, etc.) and pull factors in urban areas (i.e. job opportunity, high levels of wage, education opportunities, better living standard, etc.) (Lee, 1986; Ravensteins, 1989; and Stark, 1991). According to the 2009 census, the Mekong Delta takes the lead in ratio of migrant workers (46‰), followed by the Central Coast with a ratio of 46‰. Almost all migrant workers leave for economic hubs in Eastern South Vietnam, especially HCMC and Bình Dương Province (Yearbook, 2009a). Moreover, the ratio of trained workers in the Mekong Delta is extremely low, around 9.7% as compared to the national average of 17.6% (Yearbook, 2009b). Therefore, the question is whether or not the insufficient education of migrant workers is the reason for their low income as compared to local workers in urban areas.

Section 2 of the paper presents measures to estimate income and analyzes income gap between migrant workers and local ones. Section 3 is a description of collated data. The discussion of research results will be undertaken in Section 4. Finally, some conclusions are offered in Section 5.

2. Income estimates and gap

a. Income estimates:

Factors affecting individual income are often estimated by a semi-logarithm equation developed by Mincer (1974) as follows:

$$(1)\ Y_i = \beta_0 + \sum_{j=1}^{J} \beta_j X_{ji} + \varepsilon_i$$

where Y_i denotes the income level (in form of logarithm) of an individual i; $X_{li}..X_{Ji}$ are explanatory variables for changes in Y_i; β is the estimation coefficient of explanatory variables, and ε_i is estimation error.

According the Oaxaca-Blinder decomposition technique (1973) of analyzing income gap between groups of workers, equation (1) for each group can be rewritten as follows:

$$(2)\ Y^n_i = \beta^n_0 + \sum_{j=1}^{J} \beta^n_j X^n_{ji} + \varepsilon^n_i$$

$$(3)\ Y^d_i = \beta^d_0 + \sum_{j=1}^{J} \beta^d_j X^d_{ji} + \varepsilon^d_i$$

where n and d respectively represents the group of migrant workers and the group of local ones.

However, the sampling is not random, and thus selection bias is inevitable during the estimation, and outcomes produced from equations (2) and (3) using the Ordinary Least Square (OLS) may be inappropriate.

In order to dispose of sampling biases, another popular alternative method is the two-step estimation by Heckman (1979). This method has recently been employed to analyze income gap between two groups of workers or households, etc. (i.e. Perloff et al., 1998; Zhu, 2002; and Tsegai, 2007).

Based on the two-step estimation method, we have:

$$(4)\ Y^n_i = \beta^n_0 + \sum_{j=1}^{J} \beta^n_j X^n_{ji} + \gamma^n_\lambda \lambda^n_i + \varepsilon^n_i = \widehat{Y}^n + \varepsilon^n_i$$

$$(5)\ Y^d_i = \beta^d_0 + \sum_{j=1}^{J} \beta^d_j X^d_{ji} + \gamma^d_\lambda \lambda^d_i + \varepsilon^d_i = \widehat{Y}^d + \varepsilon^d_i$$

Where, λ is the Inverse Mill's ratio and defined as $\lambda = f(Z_i, \gamma_j)/F(Z_i, \gamma_j)$. If the statistical significance of estimation coefficients λ in equations (4) and (5) is other than zero, the two-step estimation method is more congruent with this study than OLS.

b. Estimation of income gap:

- Oaxaca-Blinder decomposition technique:

Suppose that the mean of ε^n and ε^d is zero (Fang & Sakellariou, 2011), the income gap can be calculated as follows:

Through the equation (6), it is apparent that income gap are constituted by four factors: (a) unexplained factors, (b) factors concerning sampling biases, (c) individual characteristics, and (d) factors concerning discriminations in the labor market. However, if there is no sampling bias ($\gamma = 0$), the equation (6) just comprises (a), (c) and (d).

$$(6)\quad \Delta\widehat{Y} = \widehat{Y}^n - \widehat{Y}^d = \beta^n_0 + \sum_{j=1}^{J} \beta^n_j X^n_{ji} + \gamma^n_\lambda \lambda^n_i - \left(\beta^d_0 + \sum_{j=1}^{J} \beta^d_j X^d_{ji} + \gamma^d_\lambda \lambda^d_i\right)$$

$$\Delta\widehat{Y} = (\beta^n_0 - \beta^d_0) + \left[\overline{\lambda}^d_i (\gamma^n_\lambda - \gamma^d_\lambda) + \gamma^n_\lambda (\overline{\lambda}^n_i - \overline{\lambda}^d_i)\right] + \sum_{j=1}^{J} \beta^n_j (\overline{X}^n_{ji} - \overline{X}^d_{ji}) + \sum_{j=1}^{J} \overline{X}^d_{ji} (\beta^n_j - \beta^d_j)$$

(a) *(b)* *(c)* *(d)*

Assume that there is no market discrimination, in other words, the labor productivity of two groups of workers is the same ($\overline{X}_{ji}^{n} = \overline{X}_{ji}^{d}$), Equation (6) will be adjusted in the reserve direction according to coefficients β_j (Fang & Sakellariou, 2011), that is:

$$\Delta\widehat{Y} = (\beta_0^n - \beta_0^d) + \left[\overline{\lambda}_i^d(\gamma_\lambda^n - \gamma_\lambda^d) + \gamma_\lambda^n(\overline{\lambda}_i^n - \overline{\lambda}_i^d)\right] + \sum_{j=1}^{J}\beta_j^d(\overline{X}_{ji}^n - \overline{X}_{ji}^d) + \sum_{j=1}^{J}\overline{X}_{ji}^n(\beta_j^n - \beta_j^d) \quad (7)$$

- The quantile regression model:

Income gap, whether they are calculated by OLS or Heckman methods, are mainly based on the mean of income. Meanwhile, such gap can take place at various points of the distribution of the income between two groups of workers (Christofides, Polycarpou & Vrachimis, 2010; Fang & Sakellariou, 2011; Kee, 2005). Therefore, Koenker and Bassett (1978) introduced their quantile regression model that can be employed to estimate income at each quantile of the distribution function of income variable. The model can be formulated as follows:

$$Y_i = \beta_\theta X_i' + u_{\theta i}, \qquad Quant_\theta(Y_i \mid X_i) = \beta_\theta X_i' \quad (8)$$

Where, Y_i is a dependent variable, X_i is the vector (Kx1) of independent variables, β is the estimation coefficient of the model at the quantile θ, θ is the order of quantile in the distribution function of dependent variable ($0<\theta<1$), $u_{\theta i}$ is the error; and $Quant_\theta(u_{\theta i} \mid X_i) = 0$.

This method is mainly to consider gap in income between two groups in which the glass ceiling may be expanded at the high end and the sticky floor may be reduced at the low end, as shown in Figure 1 below.

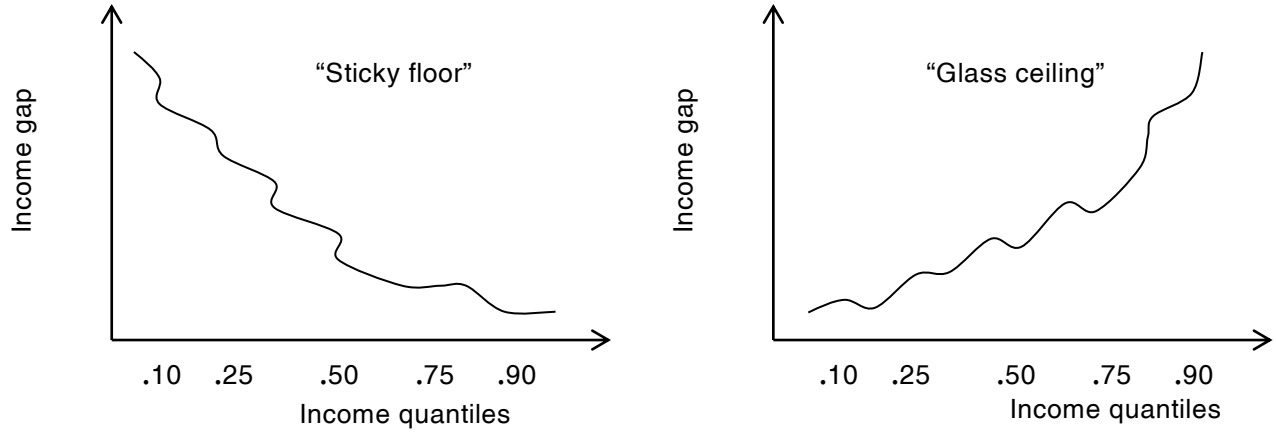


Figure 1: Description of income gap according to quantiles

3. Dataset and descriptions

The dataset is collected from 401 workers in HCMC, Vĩnh Long Province, and Cần Thơ City as from March to May 2009. Of them, 263 migrant workers come from the Mekong Delta, and 138 are local ones. Respondents are blue-collar workers, officials, street vendors, and shopkeepers.

Information about individual characteristics, human capital, reason for migration, job, income, and remittance for their families over the past twelve months is collated via direct interviews. The variable Monthly Income is determined on the basis of respondents' income earned from their jobs. The statistical results in Table 1 show that the monthly income of migrant workers is VND170,000 higher than that of local ones, equaling 0.069 point of the logarithm of monthly income. Overall, years of schooling and working experience of migrant workers are usually higher than those of local ones. It is perhaps an excuse for income gap between these two groups of workers.

Table 1: Description of observed variables

Variable	Unit	Migrant workers		Local workers	
		Mean	Standard deviation	Mean	Standard deviation
Monthly Income	VND1,000/month	2.469	1.488	2.299	1.413
Logarithm of income	-	7.674	0.50	7.605	0.48
Number of schooling years	Year(s)	10.24	3.76	9.67	2.92
Working experience	Year(s)	3.57	3.04	3.45	2.39
Gender (male)		0.54	0.49	0.33	0.47

Source: The author's survey in 2009

Table 2: Factors affecting income

Factors	Model 1		Model 2	
	Migrant workers	Local workers	Migrant workers	Local workers
Number of schooling years	0.061***	0.025*	0.061***	0.025*
	(8.16)	(1.84)	(8.15)	(1.87)
Working experience years	0.084***	0.163***	0.084***	0.155**
	(2.64)	(2.83)	(2.66)	(2.55)
(Working experience years)^2	-0.002	-0.007	-0.002	-0.006
	(-0.60)	(-1.03)	(-0.61)	(-0.90)
Gender (male)	-	-	-0.009	0.042
	-	-	(-0.18)	(0.52)
Interception coefficient	6.791***	6.915***	6.795***	6.918***
	(69.00)	(37.29)	(62.79)	(37.28)
Sampling population	263	138	263	138
P-value	0.000	0.000	0.000	0.000
R^2	0.336	0.265	0.336	0.267

Note: the bracketed figures are t-stats.

The Oaxaca-Blinder decomposition results concerning income gap of the two groups are shown in Table 3.

Table 3: Income gap according to components (equation 6)

Model	Income gap	Components		
	$\Delta\widehat{Y}$	$(\beta_0^n - \beta_0^d)$	$\sum_{j=1}^{J}\beta_j^n(\overline{X}_{ji}^n - \overline{X}_{ji}^d)$	$\sum_{j=1}^{J}\overline{X}_{ji}^d(\beta_j^n - \beta_j^d)$
1	0.074	-0.125	0.035	0.163
2	0.067	-0.123	0.034	0.157

Table 4: Income gap according to components (equation 7)

Model	Income gap	Components		
	$\Delta\widehat{Y}$	$(\beta_0^n - \beta_0^d)$	$\sum_{j=1}^{J}\beta_j^d(\overline{X}_{ji}^n - \overline{X}_{ji}^d)$	$\sum_{j=1}^{J}\overline{X}_{ji}^n(\beta_j^n - \beta_j^d)$
1	0.074	-0.125	0.002	0.197
2	0.067	-0.123	0.015	0.175

4. Analytical results

In equations (4) and (5), the Heckman procedure reveals that the statistical significance of estimation coefficient (γ) is not different from zero. Thus, OLS model can be employed instead to identify influential factors in income and estimate income gap between the two surveyed groups. Model 1 consists of two basic factors, that is, the number of schooling years and working experience years. Model 2, in fact, is Model 1 plus the factor of gender.

Overall, estimation coefficients in both models are statistically significant. The two factors of Model 1 (i.e. years of schooling and working experience) sharply affect changes in the monthly income. Most noticeably, the effect of educational level on income of migrant workers is more profound than that of local workers. Yet, if the two groups have the same working experiences, the opportunity to earn higher income seems to be weighted towards local workers rather than migrant ones. This is obvious, as local workers are often highly appreciated in terms of knowledge on the public traffic network in urban areas, and their urban lifestyle, etc.

In Model 2, the effect of gender on income is not statistically significant and this is true to both groups.

For Model 1, Table 3 shows that the monthly income of migrant workers is 7.4% higher than that of local ones. Apparently, educational level and working experience can explain 47% (0.035/0.074) of income gap between two groups. Moreover, there exists a market discrimination against migrant workers.

For Model 2, with the addition of the variable of gender, such gap tend to reduce to 6.7%. In other words, the worker's gender can help explain 8.79% [(0.074-0.067)/0.074] of income gap. In general, individual characteristics (i.e. educational level, working experience, and gender) can explain 50.7% (0.034/0.067) of income gap between the two groups of workers.

Results for equation (7) are presented in Table 4, which shows that when the working productivity of the two groups is assumed to be identical, income gap due to individual characteristics decrease substantially as compared to their role in equation (6). In other words, income gap in the equation (7) are primarily related to market discrimination. Therefore, through the two aforementioned equations, it is possible to conclude that the estimation results of equation (6) can better explain income gap between the two groups on the basis of individual characteristics.

Furthermore, as was mentioned above, the quantile regression model can be employed to estimate income gap between the two groups at certain quantiles in the distribution function of monthly income. The quantile regression results presented in Table 5 reveal that income gap between the two groups have an onward trend in tandem with income distribution (i.e. the glass-ceiling effect).

Table 5: Income gap at various quantiles

Quantile / Gap	0.10	0.25	0.50	0.75	0.90
Observed value	0.000	0.060	0.106	0.182	0.064
Model 1: (number of schooling year, working experience)					
Estimates	-0,141	-0.078	0.057	0.164	0.251
Model 2: (model 1 + gender)					
Estimates	-0.141	-0.070	0.037	0.162	0.244

Apparently, the income gap between the two groups take place in two opposite directions. Specifically, with quantiles smaller than 50% in the income distribution, the income of migrant workers is lower than local ones'. On the contrary, with quantiles larger than 50%, the income of local workers is lower than migrant ones (see Appendix 1). This can be explained as follows:

- Firstly, migrant workers with low income are mainly unskilled labor; and thus, in order to have a job to support their life, they accept a low pay which is even lower than that of a local unskilled worker.

- Secondly, migrant workers with high income are skilled labor; and beyond economic purposes, they also expect to gain other targets such as professional skills enhancement, higher education, etc. Therefore, they have opportunities to opt for a well-paid job in their destinations.

Such things have been empirically examined by Lee (1966). Overall, estimation results from Model 2

show smaller gap in income than what are found by Model 1 (see Appendix 2).

5. Conclusion

Based upon the examination of 401 workers in three provinces, it is possible to tailor some following main points:

- Years of schooling and working experience have positive effects on income of workers in general. The educational level of migrant workers is higher than that of local ones; yet, it is contrary regarding their working experience.

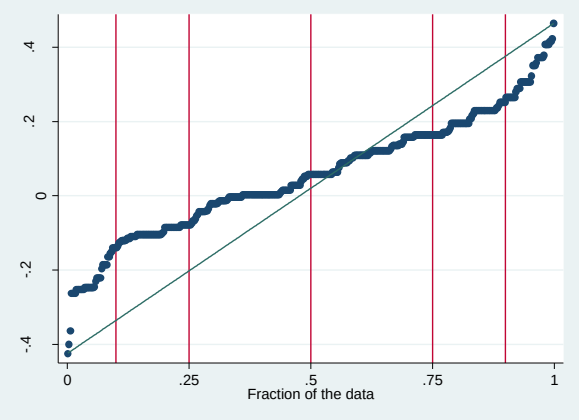
- According to the Oaxaca-Blender decomposition technique, it is apparent that the number of schooling years and working experience can explain roughly 50% of gap in monthly income.

- Additionally, the quantile regression model shows that income gap have an onward trend in tandem with income distribution (i.e. the glass-ceiling effect). It is also noticeable that of 50% of low-income workers, the income of migrant workers is lower than that of local ones; yet among high-income workers, migrant workers get a higher pay than local ones.

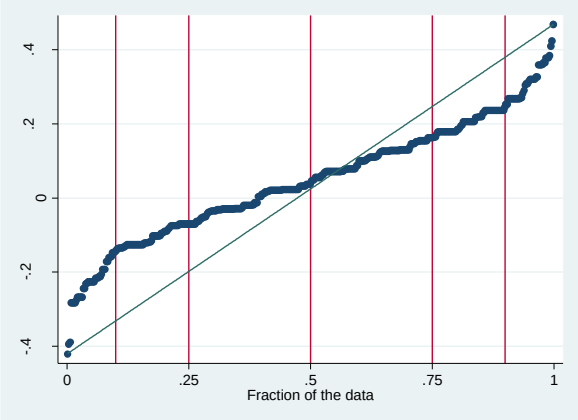
In sum, this study analyzes empirical evidences and hopefully enhances comprehension of income gap between migrant workers and local ones in the current context of Vietnam■

Appendixes

Appendix 1: Income gap according to quantiles



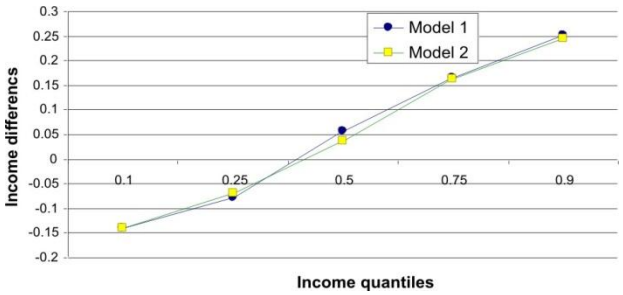
(a)



(b)

Note: (a) and (b) correspond to results of Model 1 and Model 2 respectively.

Appendix 2: Income gap according to models



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