Journal of Contemporary Issues in Business and Government Vol. 27, No. 2,2021

https://cibg.org.au/

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2021.27.02.569

Labor Market Efficiency in Indonesia: An Empirical Evidence from Household Survey

Tripitono Adi Prabowo[1*] Dyah Wulansari[2] Lilik Sugiharti[3]

[1]Universitas Airlangga,Surabaya dan Universitas Trunojoyo, Madura.

[2]Universitas Airlangga,Surabaya.

[3]Universitas Airlangga,Surabaya.

*Email : *tripitonoadiprabowo@gmail.com, dyah_wulansari@feb.unair.ac.id, lilik.soegiyono@gmail.com*

Abstract

This paper aims to measure labor markets efficiency using production frontier framework. Using Household Social and Economic Survey run by Bureau Statistical Agency, we estimate the production frontier of human capital function in determining earnings. We estimate the model since 1998 until 2014 but with missing some years of observation those are 2004, 2005, and 2011. Wes estimate the on the basis cross section data and we compare them to other periods applying Corrected Ordinary Least Square (COLS), Corrected Median Absolute Deviation (CMAD), and Maximum Likelihood function for Stochastic Frontier Analysis (SFA). The results shows that all input variables are strongly significant with positive sign. All three methods of estimation results consistent parameters both in terms of values and signs. The efficiency scores of labor markets in Indonesia are relatively very low but have increasing pattern every year.

Keywords: Labor Markets, Efficiency,SFA

JEL: J30, J24, J40

I. Introduction

Indonesia, in terms of its population, is the he fourth largest country in the world after China, India, and United States of America with more than 260 million people. As one of the main production factor of the economy, the role of population in the economic activity is strongly determined by the labor market performance. Solo (1969) re-examines hypothetically that when there is low wage, the optimum technology to maximize production process with available resources is labor intensive rather than capital intensive. This hypothesis is strengthened by the fact that most developing countries has huge number of population compared relatively by advanced economy. Moreover, most developing countries does not have abundant capital to support their economic development (Khatkhate, 1980). Balassa (1964) (Dj et al., 2019; Ghofur et al., 2021; Muhtarom, 2018)show that South East Asia has the largest

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2021.27.02.569

capital requirement among other regions in the world in 1975. The simultaneous solution to boost the economy of developing countries such as Indonesia is improving labor markets performance and increasing capital stock.

According to the Global Competitiveness Report 2019, published by World Economic Forum (WEF), which contains four aspects those are enabling environment, markets, human capital, and innovation ecosystem. Labor markets, as one of the components of markets aspect in global competitiveness index, has an issue with labor force size. Indonesia with the highest labor force size has the lowest labor markets performance rank among six greatest countries in South East Asian, and 85th rank from 140 countries in the world. It means that if Indonesia may improve the labor markets performance, it will highly contributed to the economic performance rank. One of the most concern regarding labor markets is returns to education which show how much labor paid based on their education, skills, or experience. This means labor markets efficiency in the context of how much return on human capital investment.

Table 1.1 South East Asian Labor Markets and Economic Competitiveness Rank

No	Country	Competitiveness Rank	Labor Markets Rank
1	Brunei Darussalam	56	30
2	Indonesia	50	85
3	Malaysia	27	20
4	Philippines	64	39
5	Singapore	1	50
6	Thailand	40	46

Source: Global Competitiveness Report 2019, World Economic Forum

This paper investigates labor markets performance through measuring labor markets efficiency. Efficient in using human capital investment and getting the return from the labor markets is expected by labors when accepting job offer. Using National Social and Economic Household Survey in Indonesia, this paper tries to measure how efficient labor markets in Indonesia in terms of human capital investment returns from labor markets. Landeau and Contreras (2003) and Bishop et all (2007) using frontier approach of income or wage function with human capital investment to calculate technical efficiency of labor markets. If worker invests on education or skills they will expect that they can get more than what they spent.

The construction of this paper can structured as follows: the following part is the literature survey which describe some evidence and theoretical ideas concerning labor markets efficiency. The third part is describing data and econometric model as well as estimation

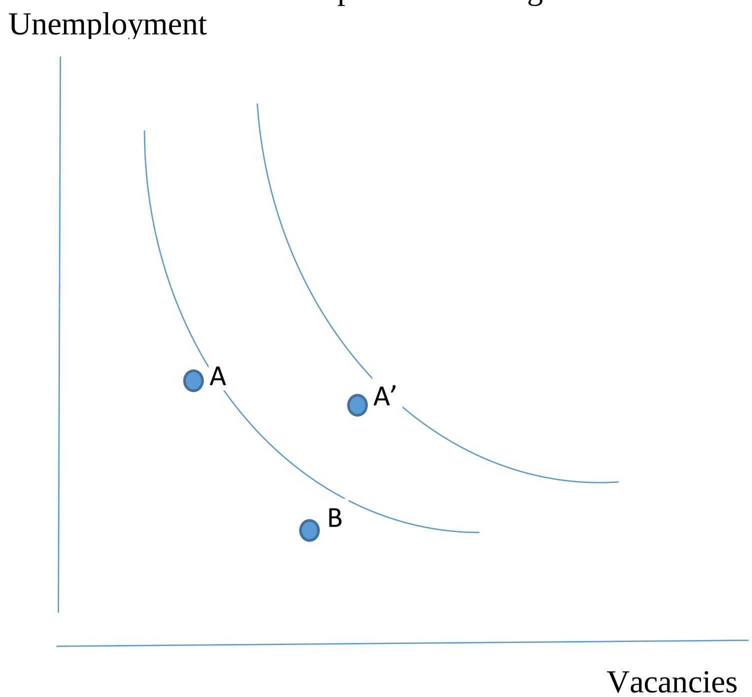
P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2021.27.02.569

techniques. The following chapter examines the estimation results and its analytical concern, and last but not least is the concluding remarks.

II. Literature Survey

The concept of labor markets efficiency is derived from two parts. The first part is how elastic new position in responding changes in unemployment and vacancies. In other words, labor markets is efficient when the number of new hired positions accommodate the number of unemployment and vacancies. Markets is effective and response to what are provided by the markets so that the equilibrium of labor demand and supply is fulfilled at all time. This idea is developed from the Beveridge curve which graphically describe the relationship of vacancies and unemployment. The Beveridge curve can be drawn as below:

Graph 2.1 Beveridge Curve



Source: Rama (2016)

Graph 2.1 shows us that shifting from point A to point A' is worsening labor market efficiency since there are more vacancies and more unemployment. On the other side, movement from point A to B is tightening without changes in efficiency of the labor markets because more vacancies and less unemployment so that more employers competitively attract workers to join with them. The way to examine the beveridge curve is matching functions. The functions connect the number of new hired workers (H), the number of job seekers (U), and the number of

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2021.27.02.569

current vacancies. Intutively, H will increase when more people are actively searching for a job and when there are more vacant positions. The function of matching can be written as follows:

$$H = h(U,V) \tag{2.1}$$

h is the matching function. Some empirical evidence try to investigate this relationship such as Rama (1998), Cotti and Drewianka (2007), and Ilmakunnas and Pesola (2003).

The second part of how to understand labor markets efficiency is by using human capital investment returns which is earnings. The labor markets is the place where investment in human capital investment such as education, experience, and or skills get paid off. Labor markets is efficient when human capital investment is as workers income expected. Labor income represents the equilibrium between labor supply and labor demand so that when factors determining income changes, it will change the equilibrium income. The equilibrium point, which is equilibrium income/wage, rely on the intersection of labor demand and supply function is the labor markets efficiency. Bishop et all (2007) derived this income equilibrium as follows:

$$L_{jk}^{D} = \theta_1^D + \theta_2^D X_{jk} + \theta_3^D w_{jk} - \mu_{jk}^D, \mu_{jk}^D \geq 0 \tag{2.2}$$

$$L_{ji}^{S} = \theta_1^S + \theta_2^S X_{ji} + \theta_3^S w_{ji} - \mu_{ji}^S, \mu_{ji}^S \geq 0 \tag{2.3}$$

Where L_{jk}^{D} and L_{ji}^{S} is the number of labor demanded for firm k in labor market j and individual decision of labor supply. The term μ_{jk}^{D} is the inefficiency for firm looking for potential qualified workers in a certain labor markets and μ_{ji}^{S} represents the inability of job seeking workers to find potential employers where they can expect what they have spent in human capital as well as immobility because the labor markets is employer's monopsony. Based on that, we may conclude that inefficiency in labor markets come from demand and supply side. So that the gap between received earnings and frontier earning represents the inefficiency of labor markets. Labor market clearing can be derived into following equation for N potential job seekers and K employers:

$$\sum_{K=1}^{K_j} L_{jk}^{D} = \sum_{i=1}^{N_j} L_{ji}^{S} \tag{2.4}$$

From the equation 2.4, market clearing equilibrium wage, we can derived the reduced form of wage earning equation as follows:

$$\ln(w_i) = \alpha + \beta X_i + \upsilon_i - \mu_i \tag{2.5}$$

Where w is the natural logarithm of wage and X is the human capital factors such as education and experience. $\upsilon_i \sim N(0, \sigma_v^2)$ is normal error, and $\mu_i \geq 0$ is earning inefficiency. This paper concerns with the application of frontier model in estimating earning function since the structure of micro data in individual and household survey in Indonesia do not contain information regarding the number of new hired positions so that the most possible techniques to estimate labor market efficiency is earning function approach. Some empirical evidence applying this

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2021.27.02.569

approach are Landeau and Dante (2003), Bishop et all (2007), Adamchik and King (2007), Angeles Diaz and Sanchez (2011), and Bazen and Waziri (2017)

III. Methodology

3.1 Data

The data used in this study is cross sectional data from annual household and individual survey held by Indonesia Bureau Statistical Agency (Badan Pusat Statistik, BPS). The data from survey are collected from all districts and municipal in Indonesia and the data is valid at district level (Kabupaten and City) but not valid at sub districs (Kecamatan) level. It means that targeted households of the survey is randomly chosen as respondent at district and municipal level. The number of respondents is vary and it depends on population size that is normally increasing every year. In some years since 2008 until 2010 the number of sample size was significantly decreasing but since 2011 the sample size is much greater and proportionately increase.

This study covers from 1998 until 2014 with some missing data for some years those are 2004, 2005, and 2011. Micro data of household survey since 2015 until 2017 does not provide the details of income composition and also the total income so that welfare is measured by spending composition. The raw data from the survey are needed to be clean by eliminating some respondents which are not consistent in answering the survey questions. This study choose respondents who are in the productive age, categorized by BPS, which is 15 until 64 years old. Any respondents who are not in this age range will be excluded. The details of descriptive statistics of the variables are presented in appendix.

3.2 Econometric Model

This paper use comparison three estimation techniques for earning function or individual workers which are Corrected Ordinary Least Square (COLS), Corrected Mean Absolute Deviation (CMAD), and Frontier Models with maximum likelihood estimation. We presents those three methods to compare the efficiency measure among the techniques. The basic model used in this model can be written as follows:

$$\ln y_i = \ln y_i^* - \mu_i, \qquad \mu_i \geq 0 \tag{3.1}$$

$$\ln y_i^* = f(x_i;\beta) + \upsilon_i \tag{3.2}$$

Where the subscript i represents individual workers observed. y_i is the scalar of earnings, x_i is the vector of input variables and in this case are highest education attained which is ranged from 0 to 6 which is 0 is no formal education certificate and 6 is bachelor's degree or higher, age, age^2, and some dummy variables such as gender which is 1 for male, 0 otherwise, working location (Loc) which is 1 for urban and 0 otherwise, and working economic sector (sector) which is 1 for agriculture sector and 0 otherwise, β is a $Jx1$ vector of the corresponding coefficient vector of input variables, and υ_i is a zero mean random error and $\mu_i \geq 0$ is labor markets inefficiency. Given input variables, the frontier function gives the maximum possible level of

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2021.27.02.569

earnings and it is stochastic because of υ_i So that the equation 3.1 empirically can be re written as:

$$\ln(earnings_i) = \alpha + \beta_1 Educ_i + \beta_2 Age_i + \beta_3 Age^2 + \beta_4 Gender_i + \beta_5 Loc_i + \beta_6 Sector_i + \mu_i \quad (3.3)$$

When we used COLS method, the equation 3.2 must be changed into:

$$\ln y_i^* = f(x_i;\beta) \quad (3.4)$$

What we miss in the equation 3.4 is the υ_i random error which is not allowed in COLS and therefore the equation 3.4 is non stochastic. If we take out the intercept from 3.4, the equation may be written as follows:

$$\ln y_i = \beta_0 + \tilde{x}_i^I \tilde{\beta} - \mu_i \quad (3.5)$$

Kumbhakar, Wang, and Horncastle (2015) give explanation COLS estimation step as written bellows:

1. Running frontier equation by using OLS technique and having this:

   $$\ln y_i = \hat{\beta}_0 + x_i^I \hat{\tilde{\beta}} + \hat{e} \quad (3.6)$$

   Where $\hat{e}$ are the OLS error terms. Since $E(\mu_i) \neq 0$, $\hat{\beta}_0$ generated from equation 3.6 is biased estimate of β_0 in 3.5. Even though, $\hat{\tilde{\beta}}$ is consistent estimate of $\tilde{\beta}$ in 3.5. so that OLS estimation for equation 3.5 generates consistent coefficients but biased intercept. At this stage we can get zero mean OLS regression residuals $\hat{e}_i$ that can be derived as:

   $$\hat{e}_i = \ln y_i - \left[\hat{\beta}_0 + \tilde{x}_i' \hat{\tilde{\beta}}\right] \quad (3.7)$$

   From equation 3.7, the value of $\hat{e}_i$ can be higher, equal, or less than 0.

2. The second stage of COLS is to adjust upward the intercept by the maximum value of $\max\{\hat{e}\}$ as consequences, the function bounds observation from above and then the error terms becomes:

   $$\hat{e}_i - \max\{\hat{e}_i\} = \ln y_i - \{\underbrace{\hat{\beta}_0 + \max\{\hat{e}_i\}} + \tilde{x}_i'\} \leq 0 \quad (3.8)$$

   And

   $$\hat{\mu}_i \equiv -(\hat{e}_i - \max\{\hat{e}_i\}) \geq 0 \quad (3.9)$$

   Where $\hat{\mu}_i$ in equation 3.9 is the predicted inefficiency for model 3.5. Technical efficiency of individual workers is can be measured by $\hat{TE} = \exp(-\mu_i)$

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2021.27.02.569

The second alternative used in this study is CMAD which is OLS regression that use mean or median absolute deviation (MAD) regression. By applying the same procedure as the COLS we can measure technical efficiency produced by MAD regression. COLS and CMAD is different in terms of estimation process where COLS regression use the average or mean of the data while CMAD use median as the passed through points.

The third method used in this paper is frontier model with maximum likelihood estimation. The model 3.5 assumes that inefficiency has distribution that is needed to estimate the model. There is half normal distribution proposed by Aigner, Lovell, and Schmidt (1977), Meeusen and van den Broeck (1977) argue there is exponential distribution, Truncated normal distribution that is proposed by Stevenson (1980), and the last but not least is Greene (1980a, b, 2003). Belotti, et all (2013) argues that distributional assumption needed for the identification of value of inefficiency term implies that the model is commonly suitable with maximum likelihood. Moreover, stochastic frontier model is conducted in two steps. The first is estimates the model coefficients $\hat{\theta}$ are generated by maximizing the log likelihood function $\lambda(\theta)$, where $\theta = \left(\alpha, \beta', \sigma_u^2, \sigma_\upsilon^2\right)$. The next step, the efficiency can be calculated through the mean of conditional distribution $f\left(u_i | \hat{\varepsilon}_i\right)$, where $\hat{\varepsilon}_i = y_i - \hat{\alpha} - x'_i \hat{\beta}$.

IV. Results

4.1 Regression Results

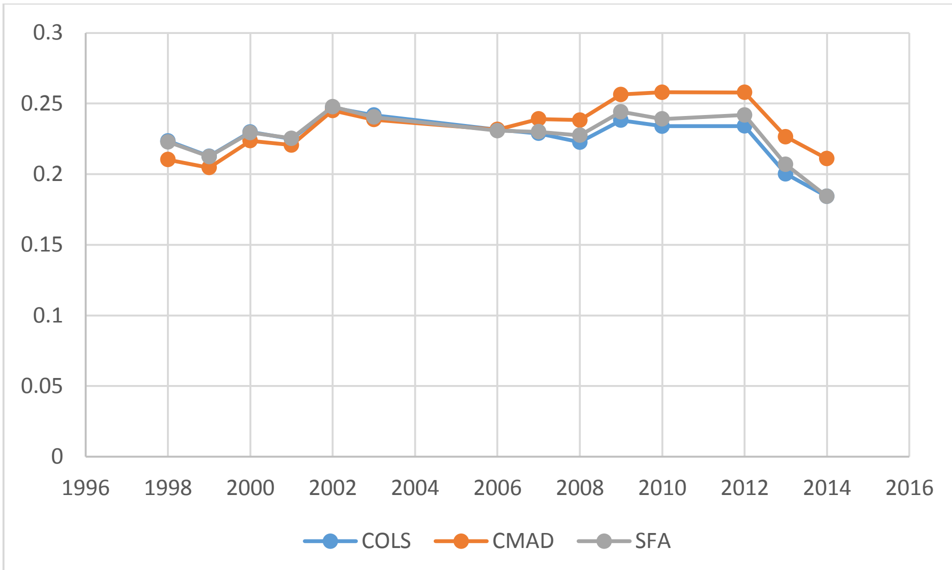
Estimation results of the production frontier model with earning as the output the human capital investment from the model 3.3 shows that all variables are statistically significant and the signs are as expected. The contribution of education as the most important issue in this discussion can be seen on the Graph 4.1. Since 1998 the role of education level in generating earnings does not have trend or moves near the average value which is 0.225 for COLS, 0.233 for CMAD, and 0.227 for Stochastic Frontier with maximum likelihood estimation. CMAD model has slightly higher predicted coefficient than other two methods. The coefficient means that increasing a level on education will increase 0.2 more percent of earnings. Off course the average contribution will different on each education level but we may say that the generally the trend is relatively constant. If we look at the graph, SFA line coincides with CMAD but COLS has higher fluctutation that other two method. The estimation considers high heteroskedasticity since cross sectional data with high range of characteristics may rise probability of of being non constant variace of error term of the estimation. Robust standard error to check and dealing with heteroskedasticity.

The contribution of education level variable has diminishing after 2012 as we look at the three lines of coefficients. According to Badan Pusat Statistik (BPS) since 2013 to 2014, the changes of nominal wage in percent had been decreasing this made the contribution of education factors to predict wages lower since there may be other factors forces income to change lower, minimum wage policy, production activity, and macroeconomic condition that was slowing

Journal of Contemporary Issues in Business and Government Vol. 27, No. 2,2021
https://cibg.org.au/
P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2021.27.02.569

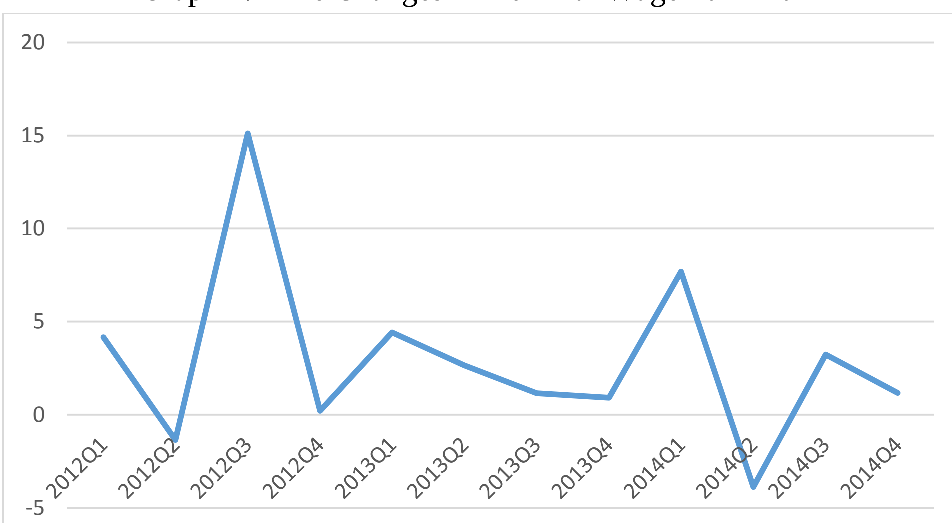
down can be some determining wage. Graph 4.2 show us the slowing down the percentage of changes in nominal wage drastically in 4th quater 2012 and remains contant ans lower after that.

Graph 4.1 Education Coefficients per Year



Source: Author's Calculation

Graph 4.2 The Changes in Nominal Wage 2012-2014



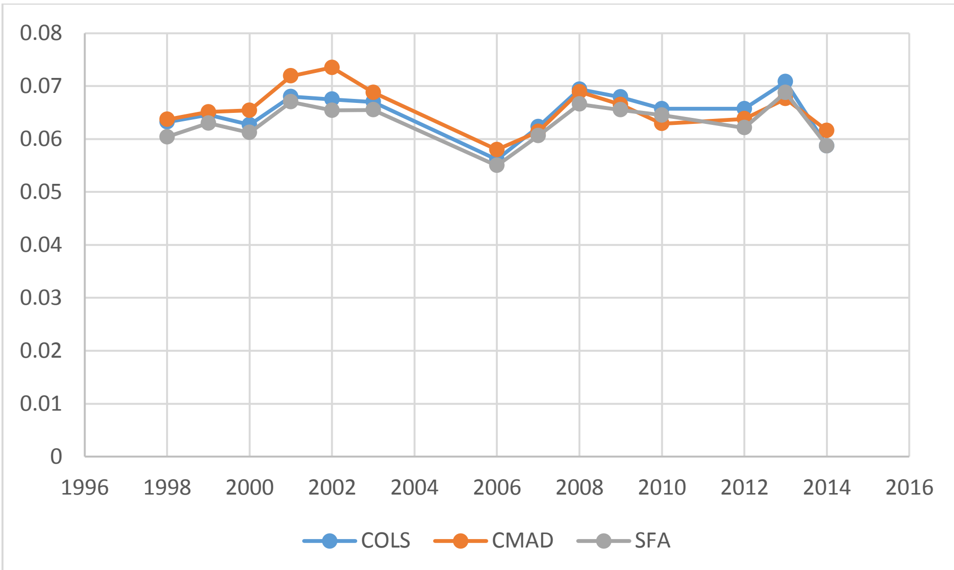
Source: Author's Calculation

The second input variable is age. Age represents physical capacity, emotional maturity, and also working experience. In equation 3.3, this variable is written in single and quadratic form since there is nonlinearity theoretically between earnings and age. Luong and Hebert (2009) uses more power on their model by using cubed and the fourth power of age variable in the model determining earnings. Age and Age^2 are strongly statistically significant at 1 percent level and

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2021.27.02.569

relatively constant at all observed year according to Graph 4.3. The coefficients of Age2 are all negative as its theory expected meaning that at a certain point age has negative effect on additional income of workers. Deelan and Euwals (2014) shows that at some points the age can still be positive in older age but depend on the working contract which sometimes allow older worker get higher payment. If we calculate the maximum point of the regression results we find the premium age, where workers get highest earnings range from 42-53 years.

Graph 4.3 Age Coefficients per Year



Source: Author's Calculation

Other variables in the models are dummy variables which are also statistically significant at all three models. Gender earnings gap is an arguing issue where there is different treatment between male and female workers. Abundant papers provide empirical evidence on gender earning gap and most of them argue that there is a gap on earnings between male and female workers. Graph 4.4 shows that there is not only statistically significant but the trend is positive meaning that the gender gap is increasing. Since 1998, the increase of gender gap in 2014 is 4,37 percent based COLS estimation, 36,8 percent for CMAD, and 8,63 percent for SFA model. Nopo, Daza, and Ramos (2011) find gender gap earnings range between 8 until 48 percent in 64 countries that in some regions such as South Asia and Sub Saharan Africa. Hypothetically, male workers more productive on strong physical type of jobs. Based on Graph 4.4, gender earning gap in Indonesia range between 0.4 until 0.5 percent meaning that male workers 0.4 or 0.5 percent higher than female workers.

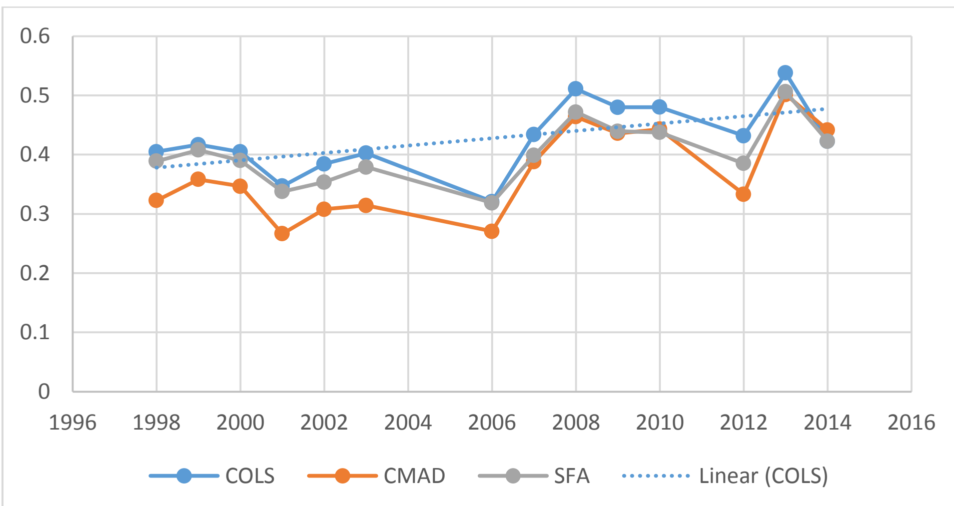
Another dummy variable is location which describe working place area those are urban and rural area. Based on the Graph 4.5 the wage gap of urban and rural is going higher. Urban

Journal of Contemporary Issues in Business and Government Vol. 27, No. 2,2021
https://cibg.org.au/

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2021.27.02.569

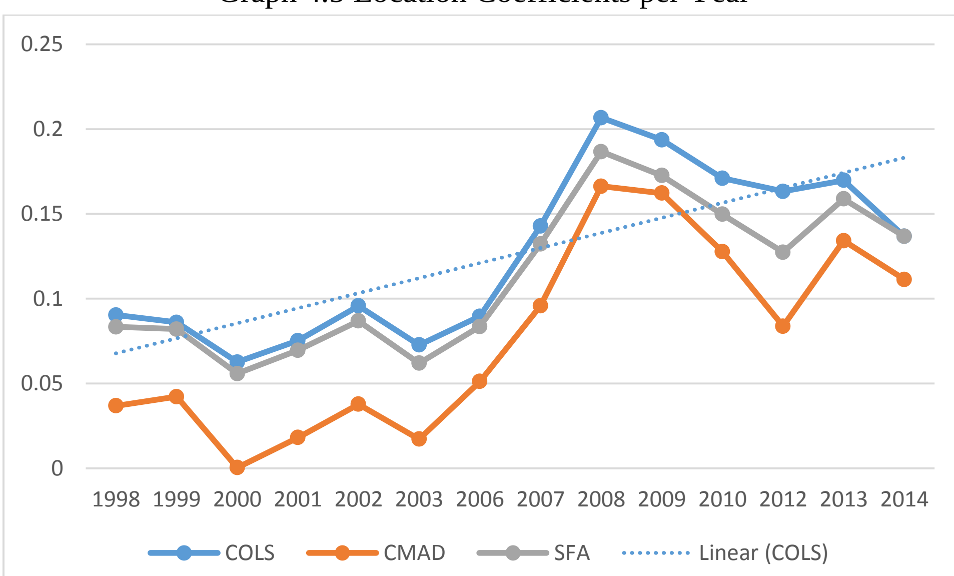
area is built from modern economic activity and most of them has higher mobility and speed of transaction since modern sector is elastic to the market demand. This is true when there is structural changes from traditional to modern economy. Modern economy, such as trade, services, manufacturing, and infrastructure, provides more flexible to response changes in markets and higher value added of production so that wage is relatively higher. This is closely connected with the Graph 4.6 showing us that traditional sector (agriculture) is paid lower than modern sector.

Graph 4.4 Gender Coefficient per Year



Source: Author's Calculation

Graph 4.5 Location Coefficients per Year

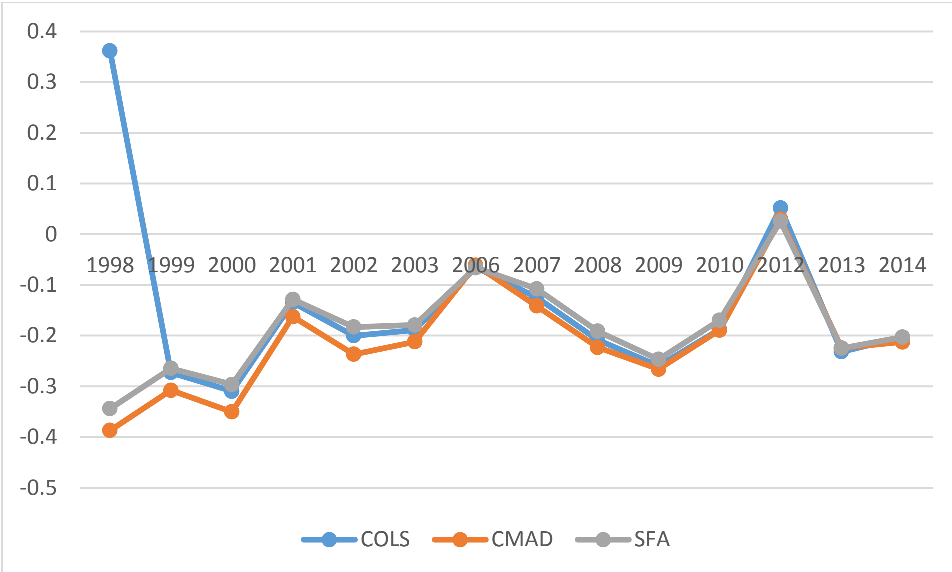


Source: Author's Calculation

Journal of Contemporary Issues in Business and Government Vol. 27, No. 2,2021
https://cibg.org.au/

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2021.27.02.569

Graph 4.6 Sector Coefficients per Year

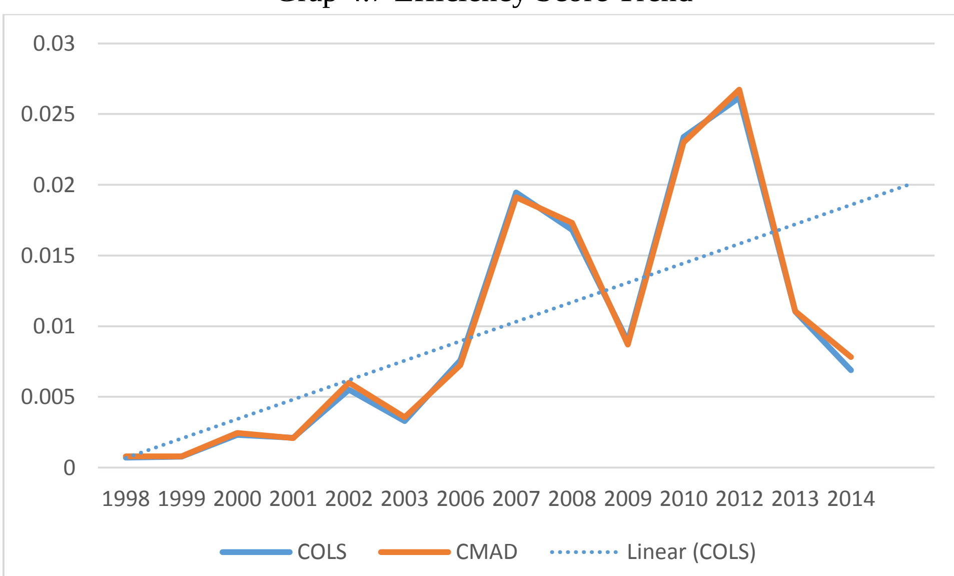


Source: Author's Calculation

4.2 Labor Markets Efficiency

The efficiency in labor markets are calculated using equation 3.5 and the value range from 0 to 1. The closer to 1 is the more efficient. Based on the calculation from regression results the efficiency score is relatively very small. The mean of technical efficiencies is less than 1 percent and maximum value is 1 or 100 percent. The difference between the two methods is only 1.29 percent. Nevertheless, the efficiency score is increasing significantly since 1998, the trend line has positive slope.

Grap 4.7 Efficiency Score Trend



Source: Author's Calculation

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2021.27.02.569

Labor markets efficiency means that the efficiency of human capital investment to generate future income so that the low score show us the low of relative return of the investment. Simulation data during estimation f the three techniques has also been done but the results is still not statistically different. Changing variables such as years of schooling, and working experience as the input variables instead of level of highest education attained and age results in the similar efficiency score which is very low.

Table 4.1 Labor Markets Efficiency Score

Tahun	COLS			CMAD		
	Mean	Min	Max	Mean	Min	Max
1998	0.000711	2.35E-07	1	0.000786	2.64E-07	1
1999	0.000767	5.11E-07	1	0.000793	5.54E-07	1
2000	0.002311	1.34E-05	1	0.002436	1.51E-05	1
2001	0.002098	2.62E-08	1	0.002077	2.75E-08	1
2002	0.005507	0.00003	1	0.006008	3.34E-05	1
2003	0.003285	2.67E-05	1	0.003561	2.98E-05	1
2006	0.007592	0.000153	1	0.007254	0.000146	1
2007	0.019454	0.000368	1	0.019121	0.000361	1
2008	0.01681	7.32E-05	1	0.017298	7.44E-05	1
2009	0.008916	3.87E-05	1	0.008699	3.68E-05	1
2010	0.02337	0.000239	1	0.023004	0.000225	1
2012	0.026165	0.000129	1	0.02673	0.000133	1
2013	0.011025	0.000117	1	0.011061	0.000106	1
2014	0.006881	3.72E-05	1	0.007811	4.31E-05	1

Source: Author's Calculation

V. Conclusion

This paper aims to measure the efficiency score of labor markets using the human capital investment return using production frontier function to estimate individual labor markets efficiency score from Indonesia household social and economic survey. The results in efficiency score of labor markets efficiency in Indonesia has relatively very low compared to other previous studies. This is supported by that Indonesia very low rank on labor markets performance according to global competitiveness report. Applying three method of estimation for production function of human capital investment those are COLS, CMAD, and maximum likelihood (SFA) results in similar score of efficiency so that the results is robust regarding the efficiency score and parameters of estimation. The coefficients of estimation performs excellent in by strongly determining the earnings variable.

There are three issues that can be followed up other studies about the efficiency of labor markets in Indonesia, there are the gender earning gap is increasing since 1998 so that to find out more deeply what drives this situation would valuable for the discussion concerning labor

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2021.27.02.569

markets and gender study. The second issue is that there is location gap earnings which is between urban and rural area which can generate inequality in the whole economy, this may be interesting to be investigated its connection with urbanization, and income inequality. The third issue is about what are the determinants of efficiency score in Indonesian labor markets. Nevertheless, the efficiency score in consistently increasing since 1998. There are some points of slowing down but the trend is positive. Since labor markets performance is the only way of population in the a country contributing to the its economic development, improvement of labor markets through some instruments bot demand and supply side must be implemented in order to optimize the role of human capital in the development process.

References

Adamchik, Vera A, and King, Arthur E. 2007. Labor Market Efficiency in Poland: A Stochastic Wage Frontier Analysis, The International Journal of Business and Finance Research ♦ Volume 1, Number 2, 2007

Aigner, D. J., C. A. K. Lovell, and P. Schmidt. 1977. Formulation and Estimation of Stochastic Frontier Production Function Models. Journal of Econometrics 6: 21–37

Angeles Diaz, Ángeles M., & Sánchez, R. (2011). Gender and potential wage in Europe: a stochastic frontier approach. International Journal of Manpower, 32(4), 410 425. doi:10.1108/01437721111148531

Balassa, B. (1964). The Capital Needs of The Developing Countries . *Kyklos, 17(2), 197–206.* doi:10.1111/j.1467-6435.1964.tb01831.x

Bazen, Stephen and Khalid Maman Waziri.2017. The Assimilation of Young Workers into the Labour Market in France: A Stochastic Earnings Frontier Approach, IZA Discussion Paper No 10841

Belotti, Federico, Silvio, Daidone, and GiuseppeI lardi. 2013. Stochastic Frontier Using Stata, The Stata Journal (2013) 13, Number 4, pp. 719–758

Bishop, John A, Andrew Grodner, Haiyong Liu, dan Jong Rong Chiou.2007. Gender Earning Differentials in Taiwan: A Stochastic Frontier Approach, Journal of Asian Economics, Vol 18, pp 934-945

Cotti, Chad, D and Scott Drewianka. 2007. Labor Market Inefficiency and Economic Restructuring: Evidence from Cross-Sectoral Data, Southern Economic Journal, Vol. 74, No. 1 (Jul., 2007), pp. 214-238

Deelen, Anja and Euwals, Rob. 2014. Do Wages Continue Increasing at Older Ages? Evidence on the Wage Cushion in the Netherlands. IZA Discussion Paper No. 8467, Available at SSRN: https://ssrn.com/abstract=2502327

Greene, W. H. 1980a. Maximum likelihood estimation of econometric frontier functions. Journal of Econometrics 13: 27–56.

———. 1980b. On the estimation of a flexible frontier production model. Journal of Econometrics 13: 101–115.

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2021.27.02.569

———. 2003. Simulated likelihood estimation of the normal-gamma stochastic frontier function. Journal of Productivity Analysis 19: 179–190

Ilmakunnas, Pekka, and Pesola Hanna.2003. Regional Labour Market Matching Functions and Efficiency Analysis, Labour 17 (3) 413–437 (2003)

Khatkhate, Deena R. 1980.Capital Scarcity and Factor Proportions in Less Developed Countries, Journal of Post Keynesian Economics, Vol. 2, No. 3 (Spring, 1980), pp. 420-429

Kumbhakar, Subal C, Hung Jen Wang, and Alan P Horncastle.2015. Practitioner's Guide to Stochastic Frontier Analysis Using Stata, Cambridge University Press

Landeau, Sergio Salas dan Contreras Dante.2003. Chilean Labor Markets Efficiency: An Earnings Frontier Approach, Estudion de Economia Vol 32 No 1, pp 87-102

Luong, May and Benoit-Paul Herbert. 2009. Age and Earnings, Perspectives, Statistics Canada, catalogue no 75-001-X

Meeusen, W., and J. van den Broeck. 1977. Efficiency estimation from Cobb–Douglas production functions with composed error. *International Economic Review* 18: 435–444

Dj, Y. R., Rosyad, S., & Muhtarom, A. (2019). Determination of Development of Small Micro Business that Enforces Deket Village, Lamongan Indonesia District. *International Journal of Research in Management, Economics and Commerce*, *09*(6), 27–29.

Ghofur, A., Dj, Y. R., Afin, R., & Muhtarom, A. (2021). COVID 19 Pandemic and Its Economic Spatial Effect : An Empirical Evidence on East Java. *Journal of Contemporary Issues in Business and Government*, *27*(3), 41–46. https://doi.org/10.47750/cibg.2021.27.03.006

Muhtarom, A. (2018). Subsisdi Of Fertilizers, Government Expenditure, Level Of Education, Ratio Of Range And Land For Agricultural Production (District Agricultural Studies - East Java 2010-2016 With Robust Test Method Analysis LAD Least Absolout Deviation). *MediaTrend*, *13*(1), 82–89. https://doi.org/10.21107/mediatrend.v13i2.3923

Nopo, Hugo, Nancy Daza, and Johanna Ramos.2011. Gender Earnings Gap In The World, IZA Discussion Paper No 5736.

Rama, Martin. 1998. How Bad Is Unemployment in Tunisia? Assessing Labor Market Efficiency in a Developing Country, The World Bank Research Observer, Vol. 13, No. 1 (Feb., 1998), pp. 59-77

Solo, Robert. (1969). Capital and Labor Intensive Technology in Developing Countries, Journal of Economic Issues, 3:4, 96-103, DOI: 10.1080/00213624.1969.11502933

Stevenson, R. E. 1980. Likelihood functions for generalized stochastic frontier estimation. Journal of Econometrics 13: 57–66

Winsten, C. (1957). Discussion on Mr. Farrell's Paper," Journal of the Royal Statistical Society. Series A (General), 120, 282–4

https://cibg.org.au/

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2021.27.02.569

Appendix 1: Descriptive Statistics: Location

Year	Location	Freq.	Percent	Total Obs.
1998	Rural	50,265	45.41	110,691
	Urban	60,426	54.59	
1999	Rural	54,300	50.06	108,462
	Urban	54,162	49.94	
2000	Rural	44,946	42.27	106,332
	Urban	61,386	57.73	
2001	Rural	36,586	35.58	102,820
	Urban	66,234	64.42	
2002	Rural	35,417	32.75	108,141
	Urban	72,724	67.25	
2003	Rural	35,834	34.47	103,961
	Urban	68,127	65.53	
2006	Rural	49,844	39.45	126,356
	Urban	76,512	60.55	
2007	Rural	136,663	50.33	271,510
	Urban	134,847	49.67	
2008	Rural	31,500	47.15	66,806
	Urban	35,306	52.85	
2009	Rural	30,872	46.47	66,428
	Urban	35,556	53.53	
2010	Rural	31,163	47.19	66,042
	Urban	34,879	52.81	
2012	Rural	60,239	36.18	166,512
	Urban	106,273	63.82	
2013	Rural	176,039	51.15	344,183
	Urban	168,144	48.85	
2014	Rural	235,024	54.46	431,536
	Urban	196,512	45.54	

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2021.27.02.569

Appendix 2 Descriptive Statistics: Gender

Year	Gender	Freq.	Percent	Total Obs.
1998	Male	77,677	70.17	110,691
	Female	33,014	29.83	
1999	Male	75,432	69.55	108,462
	Female	33,030	30.45	
2000	Male	72,764	68.43	106,332
	Female	33,568	31.57	
2001	Male	72,288	70.31	102,820
	Female	30,532	29.69	
2002	Male	75,264	69.60	108,141
	Female	32,877	30.40	
2003	Male	72,504	69.74	103,961
	Female	31,457	30.26	
2006	Male	87,232	69.04	126,356
	Female	39,124	30.96	
2007	Male	187,701	69.13	271,510
	Female	83,809	30.87	
2008	Male	44,545	66.68	66,806
	Female	22,261	33.32	
2009	Male	43,941	66.15	66,428
	Female	22,487	33.85	
2010	Male	43,693	66.16	66,042
	Female	22,349	33.84	
2012	Male	109,919	66.01	166,512
	Female	56,593	33.99	
2013	Male	231,458	67.25	344,183
	Female	112,725	32.75	
2014	Male	282,090	65.37	431,536
	Female	149,446	34.63	

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2021.27.02.569

Appendix 3 Descriptive Statistics: Education

1998	education	Freq.	Percent
0	No School	14,506	13.10
1	Elementary Level	28,694	25.92
2	Junior High School	15,648	14.14
3	Senior High School	38,105	34.42
4	One to Three Year Diploma	6,557	5.92
5	Undergraduate Degree	6,894	6.23
6	POSTGRADUTE LEVEL	287	0.26

1999	education	Freq.	Percent
0	No School	15,719	14.49
1	Elementary Level	29,183	26.91
2	Junior High School	15,402	14.20
3	Senior High School	35,121	32.38
4	One to Three Year Diploma	6,289	5.80
5	Undergraduate Degree	6,453	5.95
6	POSTGRADUTE LEVEL	295	0.27

2000	education	Freq.	Percent
0	No School	18,340	17.25
1	Elementary Level	25,868	24.33
2	Junior High School	15,243	14.34
3	Senior High School	34,349	32.30
4	One to Three Year Diploma	5,632	5.30
5	Undergraduate Degree	6,679	6.28
6	POSTGRADUTE LEVEL	221	0.21

2001	education	Freq.	Percent
0	No School	10,014	9.74
1	Elementary Level	23,639	22.99
2	Junior High School	16,465	16.01
3	Senior High School	37,597	36.57
4	One to Three Year Diploma	6,908	6.72
5	Undergraduate Degree	7,826	7.61

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2021.27.02.569

6	POSTGRADUTE LEVEL	371	0.36

2002	education	Freq.	Percent
0	No School	9,383	8.68
1	Elementary Level	24,443	22.60
2	Junior High School	17,571	16.25
3	Senior High School	38,882	35.95
4	One to Three Year Diploma	8,291	7.67
5	Undergraduate Degree	9,094	8.41
6	POSTGRADUTE LEVEL	477	0.44

2003	education	Freq.	Percent
0	No School	10,505	10.10
1	Elementary Level	21,479	20.66
2	Junior High School	16,746	16.11
3	Senior High School	39,142	37.65
4	One to Three Year Diploma	7,281	7.00
5	Undergraduate Degree	8,389	8.07
6	POSTGRADUTE LEVEL	419	0.40

2006	education	Freq.	Percent
0	No School	9,937	7.86
1	Elementary Level	24,479	19.37
2	Junior High School	20,378	16.13
3	Senior High School	46,912	37.13
4	One to Three Year Diploma	10,197	8.07
5	Undergraduate Degree	13,595	10.76
6	POSTGRADUTE LEVEL	858	0.68

2007	education	Freq.	Percent
0	No School	37,232	13.71
1	Elementary Level	75,208	27.70
2	Junior High School	48,417	17.83
3	Senior High School	76,574	28.20
4	One to Three Year Diploma	13,256	4.88
5	Undergraduate Degree	19,518	7.19
6	POSTGRADUTE LEVEL	1,305	0.48

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2021.27.02.569

2008	education	Freq.	Percent
0	No School	11,215	16.79
1	Elementary Level	17,452	26.12
2	Junior High School	11,158	16.70
3	Senior High School	18,889	28.27
4	One to Three Year Diploma	3,118	4.67
5	Undergraduate Degree	4,657	6.97
6	POSTGRADUTE LEVEL	317	0.47

2009	education	Freq.	Percent
0	No School	10,630	16.00
1	Elementary Level	17,393	26.18
2	Junior High School	10,940	16.47
3	Senior High School	18,951	28.53
4	One to Three Year Diploma	3,153	4.75
5	Undergraduate Degree	4,994	7.52
6	POSTGRADUTE LEVEL	367	0.55

2010	education	Freq.	Percent
0	No School	10,195	15.44
1	Elementary Level	17,111	25.91
2	Junior High School	10,955	16.59
3	Senior High School	19,294	29.21
4	One to Three Year Diploma	2,985	4.52
5	Undergraduate Degree	5,163	7.82
6	POSTGRADUTE LEVEL	339	0.51

2012	education	Freq.	Percent
0	No School	11,584	6.96
1	Elementary Level	28,738	17.26
2	Junior High School	25,036	15.04
3	Senior High School	61,002	36.64
4	One to Three Year Diploma	11,204	6.73
5	Undergraduate Degree	26,584	15.97
6	POSTGRADUTE LEVEL	2,364	1.42

2013	education	Freq.	Percent
0	No School	51,961	15.10

https://cibg.org.au/

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2021.27.02.569

1	Elementary Level	94,965	27.59
2	Junior High School	58,099	16.88
3	Senior High School	96,573	28.06
4	One to Three Year Diploma	11,562	3.36
5	Undergraduate Degree	28,335	8.23
6	POSTGRADUTE LEVEL	2,688	0.78

2014	**education**	**Freq.**	**Percent**
0	No School	70,074	16.24
1	Elementary Level	123,266	28.56
2	Junior High School	74,969	17.37
3	Senior High School	115,707	26.81
4	One to Three Year Diploma	12,196	2.83
5	Undergraduate Degree	32,260	7.48
6	POSTGRADUTE LEVEL	3,064	0.71

Appendix 4 Descriptive Statistics:
4a. Earnings

Year	Mean	Std. Dev.	Obs
1998	307427.8	1515903	110,691
1999	399859.1	2292654	108,462
2000	427689.9	1322024	106,332
2001	653792.5	2449312	102,820
2002	711572.6	1329021	108,141
2003	785435.8	1343246	103,961
2006	1028049	1484487	126,356
2007	933572.2	928658.6	271,510
2008	1017229	1186823	66,806
2009	1073952	1211722	66,428
2010	1172768	1263465	66,042
2012	1825145	2020156	166,512
2013	1678683	2195270	343,994
2014	1680803	2316581	431,536

4b. Age

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2021.27.02.569

Year	Mean	Std. Dev.	Obs
1998	33.73305	11.21139	110,691
1999	34.0672	11.38109	108,462
2000	34.74698	11.85775	106,332
2001	33.45297	10.94877	102,820
2002	33.88162	11.05321	108,141
2003	34.45443	11.17422	103,961
2006	34.405	11.04295	126,356
2007	36.51533	12.39844	271,510
2008	36.04976	12.19955	66,806
2009	36.87008	12.33272	66,428
2010	37.47066	12.41986	66,042
2012	35.64442	11.36564	166,512
2013	39.71645	12.97937	343,994
2014	40.27869	13.22694	431,536