RESEARCH ARTICLE

Wage Gaps in the Philippines: A Decomposition Analysis

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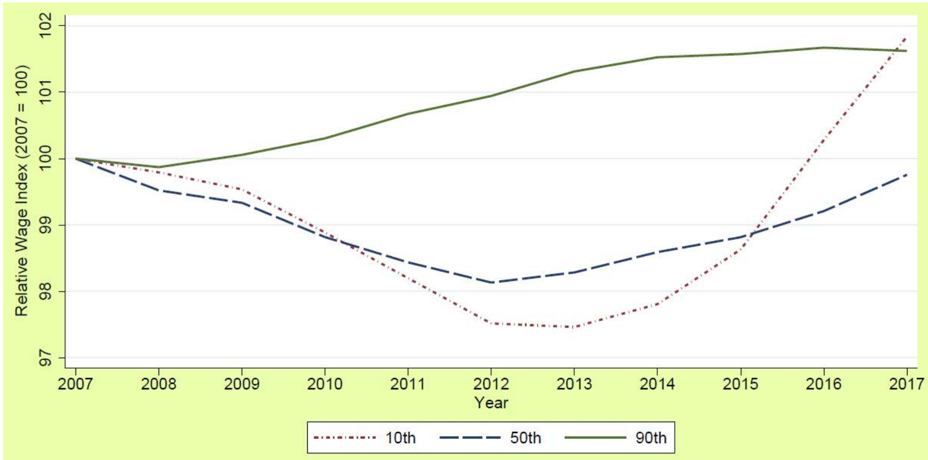
The data show that, overall, the gaps between the 90th- and 10th-percentile average real wages have changed over time. The 90th-percentile average wage steadily increased from 2007 to 2017, while the 10th-percentile average increased quite drastically after 2013. In this paper, we aim to analyze the changes in these real wage differentials further to have a better understanding of the factors that may affect the wage distribution, specifically the 90/10, 90/50, and 50/10 wage gap groupings, by employing a simple wage gap analysis and the Oaxaca–Blinder decomposition on the October rounds of the Philippine Labor Force Survey from 2007 to 2017. We find that variables included in the study, namely, *age*, *gender*, *location*, *education*, and *sector*, barely explain the differences in the mean wage levels of the different gap groupings. Albeit small, when we consider the size of the wage differential collectively explained by the model, *education* has the greatest influence, followed by *location* and *sector*. The contribution of *education* is greatly observed in the 90/10 wage gap as compared to the other two groupings. Meanwhile, for *location*, a significant contribution is observed in college and high school graduate categories.

Key Words: wage inequality; decomposition; labor market; labor economics

JEL Classifications: J010, J310

The average real wage across the distribution varies from 2007 to 2017.[1] Figure 1 shows that (1) the average wage for the 90th percentile steadily increased throughout the period covered; (2) for the 10th percentile, it sharply increased only after 2013; and (3) for the 50th percentile, it dropped from 2007 to 2012 then reversed upward towards 2017, but still with a lower end value relative to beginning value in 2007.[2] These trends may provide useful insights to understand and analyze probable factors that influence changes in wage gaps across wage distributions over time.

In the Philippines, wage inequality and wage differentials have been observed in previous studies such as Dacuycuy (2006), Hasan and Jandoc (2010), Dacuycuy and Dacuycuy (2012), Sakellariou (2012), Conchada et al. (2019), Valenzuela et al. (2017), and Chow, Dabbay, and Sauler (2019) among others.



Source: Chow, Dabbay, & Sauler (2019).

Figure 1. Relative Wage Changes at Selected Percentiles: 2006 CPI*

Using nonparametric and parametric approaches on the Philippine Labor Force Survey (LFS), the wage gap between the upper and lower deciles (or 90/10) has grown from 1988 to 1995 due to higher returns to education of workers in the 90^{th} decile and differences in work experience between the two groups (Dacuycuy, 2006). Similarly, Sauler and Tomaliwan (2015) find that workers in the upper income quantiles gain higher returns to education. Furthermore, the contribution of education to wage inequality in 1995 is relatively lower than in 1988 (Dacuycuy & Dacuycuy, 2012).

From a macroeconomic perspective, Hasan and Jandoc (2010) find that, instead of trade liberalization, the major drivers of growing wage gaps from 1994 to 2000 seem to be the changes in economy-wide returns to education and industry membership.

By employing unconditional quantile regression in analyzing the wage growth and inequality in the Philippines from 2001 to 2006, Sakellariou (2012) finds that real earnings of male workers have greatly declined from 2001 to 2006 across all wage distributions. However, male workers in Manila, the country's capital, seem to deviate from others. Sakellariou (2012) points out that significant changes to the returns are mostly concentrated at the top of the earnings distribution, and workers experience the benefits of being employed in Manila.[3]

Using the 2018 LFS data, Conchada et al. (2019) reveal that variations in wage and labor force participation rate between males and females are primarily due to gender-specific attributes, with female workers receiving lower returns. Engcong et al. (2019) also show that the increase in the pay gap between men and women comes from differences in primary occupation and educational attainment.

Chow, Dabbay, and Sauler (2019) apply simple regression and standard variance decomposition method on LFS data from 2007 to 2017 in the upper-tail distribution. The results show that the wage gap among women and among National Capital Region (NCR) workers is greater than among men and among non-NCR workers, respectively. This gap is largely due to differences in education.

As an extension to Chow, Dabbay, and Sauler (2019), we further explore and analyze the determinants of changes in wage differentials in the Philippines from 2007 to 2017. We aim to record recent trends in the labor market performance of workers and, following Fortin and Lemieux (2015), include *education*, *gender*, regional *location*, and types of *sectors* as explanatory variables. We perform a simple regression wage gap analysis and use Oaxaca's (1973) and Blinder's (1973) decomposition method to determine the individual contributions of observable and measurable variables to wage differentials between two groups.

In Section 2, we present the survey data and discuss the methodologies employed in decomposing wage gap. In Section 3, we discuss relative wage changes. In Section 4, we present our results and analysis, and in Section 5, we provide a summary of our findings, conclusion, and recommendations.

Data and Methodology[4]

We use the 2007 to 2017 October rounds of the Philippine LFS undertaken by the Philippine Statistics Authority (PSA)[5] to gather relevant data on labor market activities of the working population (restricted to the 15–64 age group), with the sample size ranging from 29,300 to 36,400 wage earners. It is a representative multistage survey that uses the sampling frame of the Integrated Survey of Households (ISH; Dacuycuy, 2006). We apply the same filtering criteria done by Chow, Dabbay, and Sauler (2019) but include agricultural workers as part of the *sector* category. In addition, we adjust the *education* categories to account for certificate courses (versus 4-year diploma course having the same title) and K-12 year levels to synchronize with the previous survey years. To ensure comparability, we use the Consumer Price Index (CPI) for each region to obtain the real wages, with 2006 as the base year. One shortcoming of the LFS is that education is merely in terms of highest educational attainment and not the years of schooling, which prevents us from constructing the Mincerian method of potential labor market experience (age − years of schooling − 6).

We also classify the data according to *region*, *gender*, *location, education*, and *sector* for the purpose of determining, if there are any, changes in wage differentials per category. Majority of the wage earners are from non-NCR (82%), males (60%), high school undergraduates and below (31.8%) followed by high school graduates (30.9%), and belonging to the service *sector* (62%). These values are shown in Table 1.

The overall average daily real wage amounts to Php 289.32 in 2017, which is roughly Php 18.00 greater than Php 270.94 in 2007. As seen in Table 1, on average, female workers earn higher than male workers, for all the years included in the study. The same can be observed for NCR workers, who earn higher than non-NCR workers. As may be expected, college graduates earn the highest compared to those with lower levels of educational attainment. Lastly, workers in the service *sector* earn the highest followed by workers in the industry *sector*.

In decomposing wage differentials, we employ the same wage gap analysis done by Chow, Dabbay, and Sauler (2019) but accounting for adjustments in the data set such as including the types of *sectors* in the list of explanatory variables and introduce the Oaxaca–Blinder decomposition (OBD) method to study labor

Table 1. *Summary of Statistics*

	Frequency	Percentage to Total	Ave Wage
TOTAL	362,031	100%	271.39
GENDER			
Male	217,545	60%	264.59
Female	144,486	40%	281.48
REGION			
NCR	65,855	18%	391.86
Non-NCR	296,176	82%	244.52
EDUCATION			
High school undergraduate and below	114,953	31.8%	147.08
High school graduate	111,749	30.9%	214.51
College undergraduate	44,910	12.4%	268.43
College graduate/post	90,419	25.0%	488.72
SECTOR			
Agriculture	49,522	14%	133.12
Industry	88,785	25%	262.54
Services	223,724	62%	305.41

Note. NCR = National Capital Region.

market outcomes by groups through decomposing the mean differences in log wages (Jann, 2008).

Wage Gap Analysis

As performed by Chow, Dabbay, and Sauler (2019), we apply a simple regression of log (real) wages on *age*, *gender*, *location*, *education*, and an additional variable, type of *sector*, to obtain the wage gap between two groups (90th vs. 10th, 90th vs. 50th, and 50th vs. 10th percentiles). The percentiles, which are based on the predicted values of the regression, are calculated per category. For instance, the 90th percentile of male workers is different from the 90th percentile of the female workers. The dependent variable is the natural logarithm of the daily real wage in Philippine pesos. The explanatory variables include *age*, *gender dummy*, *education dummies*, *location (region) dummies*, and *sector dummies*.[6]

Oaxaca–Blinder Decomposition

In this section, we provide a brief explanation of the OBD method in the absence of performing statistical inference, following the discussion of Jann (2008).

Suppose we let *y* represent wage, the outcome measure. We have two groups based on status: top (those in the upper 10th percentile) and bottom (those in the lower 10th percentile).

Let **x** be a vector of observable characteristics or determinants that we assume explains our outcome of interest.

Based on our regression model,

$$y_i = \begin{cases} \beta^t x_i + \varepsilon_i^t & \text{if top (t)} \\ \beta^b x_i + \varepsilon_i^b & \text{if bottom (b)'} \end{cases} \tag{1}$$

where the vectors of β estimated coefficients include the intercepts.

The difference between the mean outcomes, $\bar{y}^t$ and $\bar{y}^b$, is equal to

$$\bar{y}^t - \bar{y}^b = \boldsymbol{\beta}^t \mathbf{x}^t - \boldsymbol{\beta}^b \mathbf{x}^b, \tag{2}$$

where x^t and x^b are vectors of determinants evaluated at the average for the those belonging in the top and bottom part of the distribution, respectively.

To further illustrate, suppose there are only two observable characteristics to consider, x_1 (say *age*) and x_2 (say level of *education*), then the equation can be expanded as

$$\bar{y}^t - \bar{y}^b = \left(\beta_0^t - \beta_0^b\right) + \left(\beta_1^t x_1^t - \beta_1^b x_1^b\right) + \left(\beta_2^t x_2^t - \beta_2^b x_2^b\right), \tag{3}$$

which we can re-express as

$$\bar{y}^t - \bar{y}^b = D_0 + D_1 + D_2 \tag{4}$$

By doing this, we can show the difference of the average wage of those in the upper and lower tail of the distribution into parts: D_0 difference in the intercepts, D_1: differences in *age* (x_1) and the effect of the *age* (β_1), and D_2: differences in level of *education* (x_2) and the effect of level of *education* (β_2).

This method aims to determine how much of the overall gap or the gap specific to any one of the *explained* component, x_s, is attributable to (i) the differences in *xs*, and (ii) differences in the *unexplained* component, β*s*. Let $\Delta\mathbf{x} = \mathbf{x}^t - \mathbf{x}^b$ and $\Delta\boldsymbol{\beta} = \boldsymbol{\beta}^t - \boldsymbol{\beta}^b$, then the gap between the two outcomes can be expressed as

$$\bar{y}^t - \bar{y}^b = \Delta\mathbf{x}\boldsymbol{\beta}^t + \Delta\boldsymbol{\beta}\mathbf{x}^b \tag{5}$$

In Equation 5, the first component on the right represents the *explained* part, where the differences in the s are weighted by the coefficients of the upper tail group, and the second component on the right represents the *unexplained* part, where the differences in the coefficients are weighted by the **x**s of the lower tail group.[7]

The standard application of the OBD technique divides the wage gap between upper and lower groups into a part that is explained by differences in determinants of wages such as *age*, *gender*, *education*, *location*, and *types of sectors* and a part that cannot be explained by such group differences.

This method is performed by running a regression using STATA 15, where the dependent variable is the log of real wages and the independent variables are *age*, *gender* dummy, *location* dummies, *education* dummies, and *sector* dummies. This shows if *explained (identified)* or *unexplained (unidentified)* factors determine the differences in log wages between two different groups according to quantiles. The analysis per quantile is further categorized by *gender*, by *location*, by *education*, and by *sector*.

In applying the OBD method, the data are grouped according to 1) different combinations between quantiles as a whole and between quantiles based on groupings 2) by *gender*, 3) by *location*, 4) by *education*, and 5) by *sector*. The variable in which the grouping is based on is excluded from the model, and the *explained* factors are the other variables included in the analysis and the *unexplained* factors are those we did not identify in this study.

These methods are mutually exclusive, and the results from each method can be taken and interpreted independently.

Trends in Relative Wage Changes

Based on the process performed by Chow, Dabbay, and Sauler (2019) and Fortin and Lemieux (2015), we look at the relative wage changes for the 10th, 50th, and 90th percentiles of the distribution from 2007 to 2017. The three (3) wage percentiles are normalized to 100 in the base year to better illustrate the relative wage changes at different points of the distribution.

Figure 2 shows the general increase in the relative wage changes of NCR workers at the 10th, 50th, and 90th percentiles. However, for the 10th percentile, we see a notable decline from 2010 to 2012 followed by a steep increase until 2017.

For non-NCR, Figure 3 shows that only the workers in the 90th percentile register higher relative wage changes in 2017 than the base year (2007). Workers in the 10th and 50th percentiles have breached the 2007 real wage level in 2016 and 2017, respectively.

Figure 4 shows that the relative wage changes of workers who finished college at the 90th percentile increased from 2007 to 2017 and maintained a wide gap between the 50th and 10th percentiles. This behavior is close to the overall trend observed in Figure 1. The 10th percentile shows a deep plunge from 2010 while the 50th merely hovers around the baseline from 2014 to 2017.

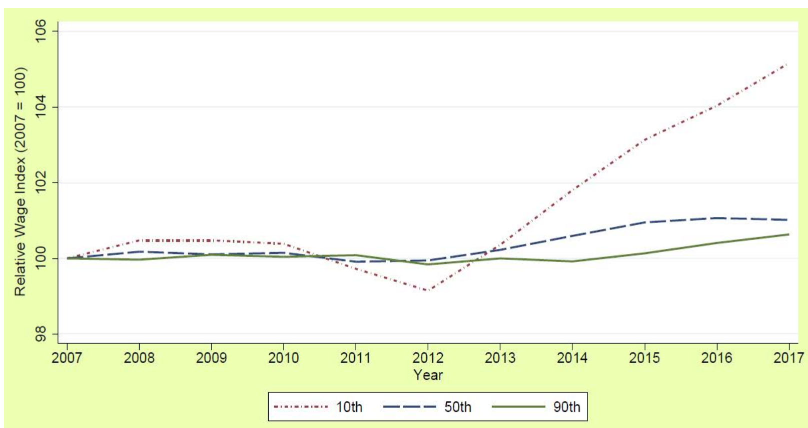


Figure 2. NCR Relative Wage Changes at Selected Percentiles: 2006 CPI

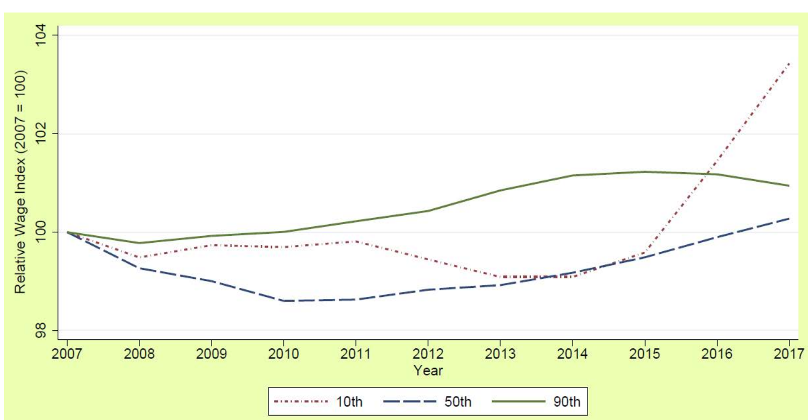


Figure 3. Non-NCR Relative Wage Changes at Selected Percentiles: 2006 CPI

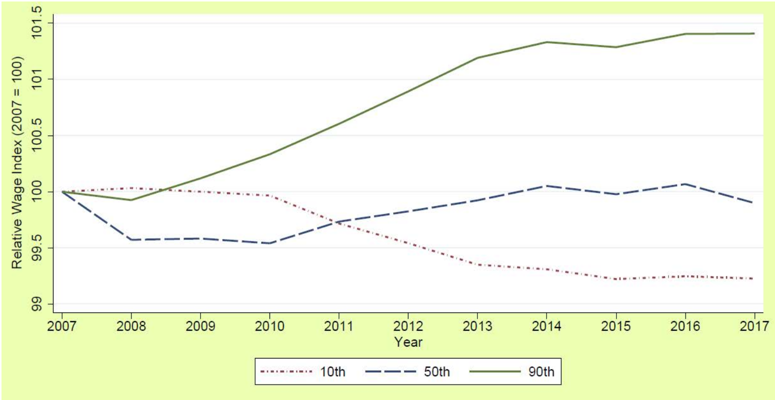


Figure 4. College Graduates Relative Wage Changes at Selected Percentiles: 2006 CPI

Figure 5. High School Graduates Relative Wage Changes at Selected Percentiles: 2006 CPI

Figure 6. Agriculture Sector Relative Wage Changes at Selected Percentiles: 2006 CPI

Figure 7. Industry Sector Relative Wage Changes at Selected Percentiles: 2006 CPI

Figure 8. Service Sector Relative Wage Changes at Selected Percentiles: 2006 CPI

Meanwhile, in Figure 5, relative wage changes of high school graduates across all percentiles exhibit higher real wage in 2017 than in 2007. Starting 2013, real wages in the 10th, 50th, and 90th percentiles show an increasing trend.

Looking at the relative wage change for workers in the agriculture *sector*, Figure 6 shows that workers at the 50th and 10th percentiles exhibit higher real wage in 2017 relative to the baseline. For the industry *sector* in Figure 7, all the percentiles show a drop in the real wage from 2007, with a notable dip for the 10th percentile in 2011. Lastly, for the service *sector*, Figure 8 shows that only the 50th percentile has a lower real wage in 2017 compared to the base year. The service *sector* closely resembles the overall trend, particularly for the 90th and 50th percentiles.

Key Observations

The trends of female, non-NCR, and service *sector* workers similarly follow the overall trend in Figure 1. This may not be surprising since 80% of the labor market work in non-NCR and roughly 60% belong to the service *sector*, which records the highest average hourly wage.

Based on these graphs, we can also see how the actual gaps between percentiles change throughout the years. Generally, we notice that from 2013 to 2017, all selected percentiles show an increasing trend but only the 10th and 90th percentiles exceed the 2007 base year real wage level. The steep increase at the 10th percentile is seen in all the factors observed except college graduates while the steady increase at the 90th percentile is also seen in all the factors except the industry *sector*.

Considering these trends in relative wage changes for the latter period of the study, we observe that the 90/10 and 90/50 wage gaps have declined. In the succeeding sections, we delve deeper into understanding how much of the observed variables explain the inequalities between the percentiles.

Results and Analysis[8]

Wage Gap Analysis

In generating the results, we primarily run the methods to different combinations of groups by quantiles to decompose the wages of the overall data. However, our discussion focuses on the 90/10, 90/50, and 50/10 wage gap groupings.[9] Secondarily, we also try to analyze the quantiles after categorizing them according to specific *gender*, *location*, *education*, and *sector*.

Figure 9 shows the 90/10 wage gap according to the different categories. The wage gaps according to *gender* and *location* increased from 2007 to 2012 but steadily declined from 2012 to 2017. Furthermore, the wage gap among females and among non-NCR workers is greater than the wage gap among their respective counterparts. Meanwhile, from 2007 to 2017, the wage gap among high school graduates is greater than the wage gap among college graduates. We also note that the college graduate subcategory is the only group that shows an increase in wage gap, albeit small, from 2007 to 2017.

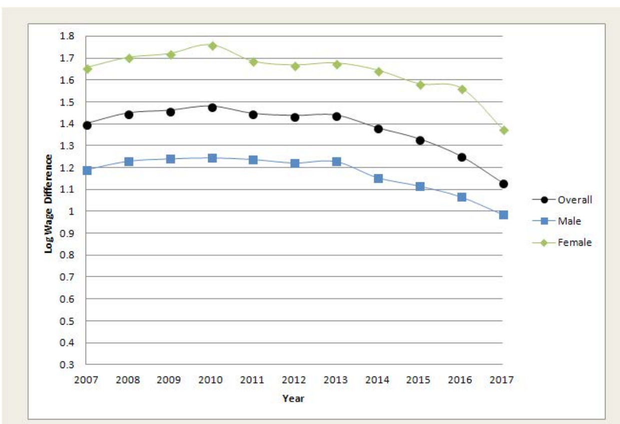


Figure 9a. 90/10 Wage Gap According to Gender

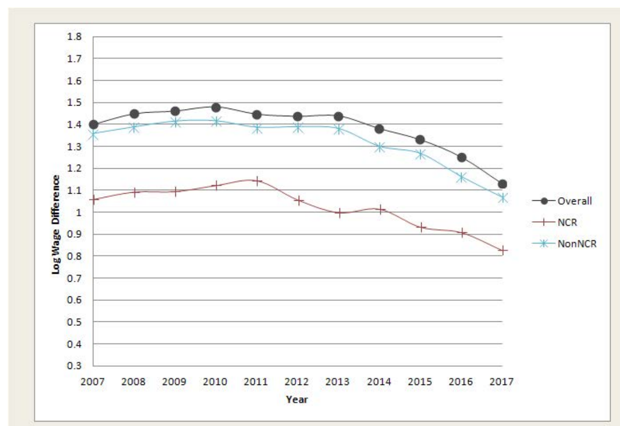


Figure 9b. 90/10 Wage Gap According to Location

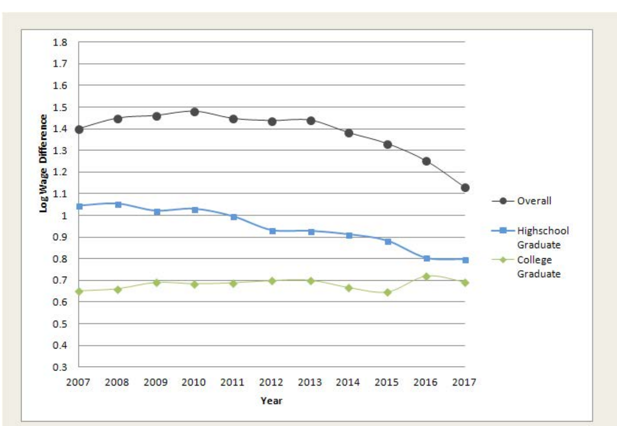


Figure 9c. 90/10 Wage Gap According to Education

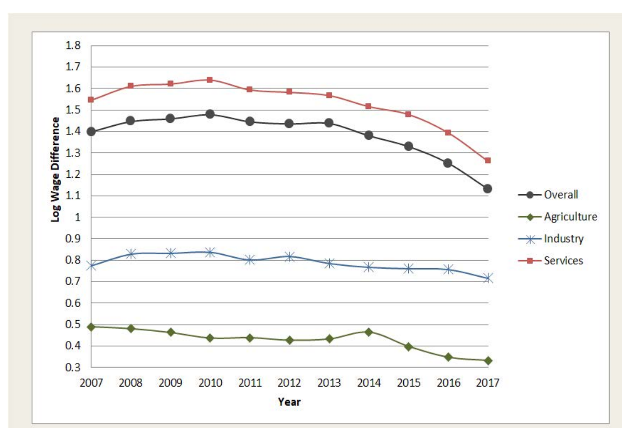


Figure 9d. 90/10 Wage Gap According to Sector

Figure 9. 90/10 Wage Gap According to Gender, Location, Education, and Sector

For the types of *sectors*, the service *sector* exhibits the highest wage gap among its workers followed by the industry *sector*. For agriculture, the decline of the wage gap is gradual, unlike the steep decline in the industry *sector* after 2010.

Collectively looking at the graphs in Figure 9, the overall 90/10 gap is greatly influenced by the gaps observed among female, non-NCR, and service *sector* workers. The varying 90/10 wage gaps among these subgroups in each category may be attributed to underlying causes such as experience or existing labor policies. For instance, we can say that there may be a premium in education for workers in the non-NCR region or experience for workers in the service *sector*.

The 90/50 wage gap roughly shows the same behavior as observed in the 90/10 wage gap. The 90/50 gap experienced an increase from 2007 to 2012 and a decline afterward. The 90/50 gaps among female, non-NCR, high school graduate, and service *sector* workers are also higher than their respective counterparts.[10]

The 50/10 wage gap paints a different picture relative to the other two wage gap groupings. In Figure 10, the 50/10 gap among the respective subgroups follows a downward trend for *gender*, *location*, *education*, and *sector*, except for the college graduate subgroup. However, the magnitude of the gap has remained the same, where the 50/10 wage gap for female, non-NCR, high school graduate, and service *sector* workers is higher than their respective counterparts.

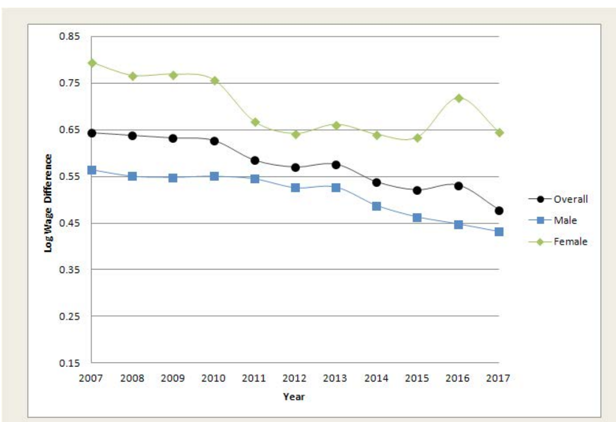


Figure 10a. 50/10 Wage Gap According to Gender

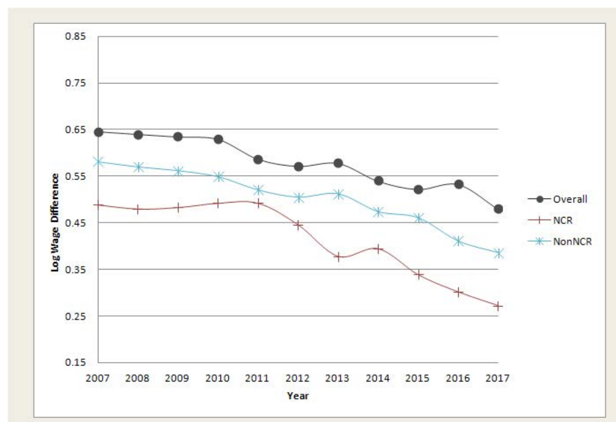


Figure 10b. 50/10 Wage Gap According to Location

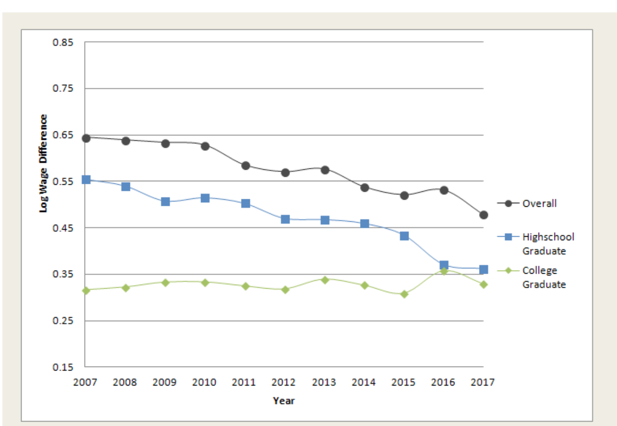


Figure 10c. 50/10 Wage Gap According to Education

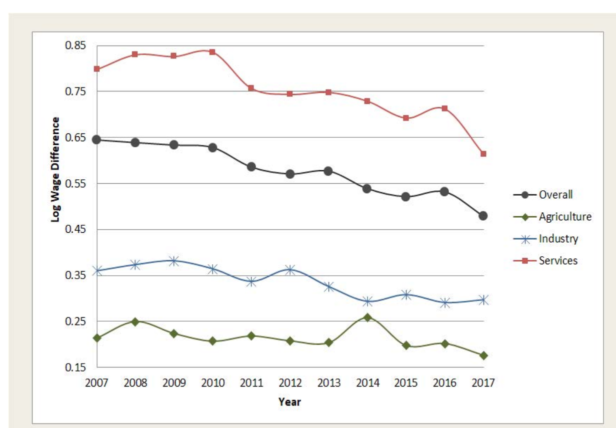


Figure 10d. 50/10 Wage Gap According to Sector

Figure 10. 50/10 Wage Gap According to Gender, Location, Education, and Sector

Key Observations

All three wage gaps measured among each category (except college graduates) record a lower spread in 2017 than in 2007, despite the spikes that occurred during the years in between. Interestingly, we find that there is a substantial difference in wages between the high-income and middle-income earners, which compose the upper half of the wage distribution. For the period covered, both the 90/10 and 90/50 wage gaps have increased around 2012 and declined afterwards, with the decline in the 90/10 greater than the 90/50. Furthermore, female workers have a wider wage differential among themselves as compared to male workers—and this is observed across all wage gap groupings. The same can be said for non-NCR and service *sector* workers against their respective counterparts.

Oaxaca–Blinder Decomposition

In this section, we explain the distribution of wage by a set of factors. For instance, variations in wages may be explained collectively by variations in *age*, *gender*, *location*, *education*, and types of *sectors* the workers belong to. The OBD method further shows the individual contribution of the predictors to the components of the decomposition and breaks down how much of the inequalities in the log hourly wage can be explained by each of the variable included in the study.

We decompose the distribution into (a) upper and lower 10th percentiles, (b) upper 10th and mid-10th percentiles, and (c) mid-10th and lower 10th percentiles, evaluating each according to overall data, *gender*, *location*, *education*, and *sector*. For example, for *gender*, we investigate the upper 10th male versus lower 10th male.[1]

The decomposition output reports the mean predictions by groups and their difference and is then divided into two parts, the *explained* and *unexplained*. The former shows how much of the variables collectively account for the wage gap. These two parts are further subdivided according to the variables included in the model.

Wage Gap Mean Differences

Some results show that the wage gap for 90/10 and 50/10 supports the observations from the wage gap analysis. For these two gap groupings, the overall data and subcategories mostly show a decrease in the differences of their respective percentile wages from 2007 to 2017 as seen in Table 2. Similarly, the size of the mean difference for female wage gap, non-NCR wage gap (except for the 50/10 gap), and service *sector* wage gap is greater than their corresponding counterparts.

In contrast to the wage gap analysis, we observe that the 50/10 gap, though decreasing from 2007 to 2017, is rather greater than the 90/50 gap. Furthermore, the OBD results for the 90/50 gap show an increasing trend from 2007 to 2017 except for the agriculture and industry *sectors*. The deviations in results may be attributed to how the differences are computed; one is based on the difference of the percentiles, while the other is based on the difference of the mean values (for example, the difference of the average log wage of the workers belonging to the upper 10th and lower 10th). In addition, only the college graduate category consistently shows an increase in spread in the mean differences of all three gap groupings, implying that the wage differential has increased.

Wage Gap Explained Collectively by Gender, Location, Education, and Sector

Table 3 shows the percentage of the mean wage difference that is explained collectively by the variables in the model. Among the three wage gap groupings, the 50/10 gap has the least portion explained by the variables in the study. This means that the difference of the average pay of a mid-wage earner and lower-wage earner is barely explained by *age, gender, location*, level of *education*, and types of *sectors*. Furthermore, in this same wage gap grouping, except non-NCR and high school graduate, the coefficient for the calculated *explained* portion of the difference is found to be statistically insignificant.

We observe that although small, the percentage of the difference *explained* by the model is greater for the 90/50 gap (upper half of the distribution) relative to the 90/10 gap. The percentage of *explained* for both gap groupings is also greater for male and industry categories, compared to their respective counterparts.

The low percentage values of the difference being *explained* by the variables included in the study entails that there must be other factors

Table 2. *Wage Gap Mean Difference for 90/10, 90/50, and 50/10 Gap Groupings*[12]

Differences	UPPER 10th > LOWER 10th (90/10)			UPPER 10th > MID 10 (90/50)			MID 10 > LOWER 10th (50/10)		
	2007	2012	2017	2007	2012	2017	2007	2012	2017
Overall	2.48	2.62	2.30	1.16	1.32	1.19	1.32	1.30	1.11
Male	2.21	2.33	2.07	1.10	1.21	1.11	1.12	1.11	0.96
Female	2.70	2.82	2.53	1.22	1.42	1.24	1.48	1.39	1.29
NCR	2.34	2.21	2.07	0.97	0.87	0.97	1.34	1.32	1.09
Non-NCR	2.46	2.61	2.26	1.19	1.38	1.22	1.28	1.23	1.04
College grad	2.04	2.17	2.17	0.92	0.97	1.00	1.12	1.20	1.17
HS grad	1.94	2.02	1.80	0.67	0.80	0.75	1.26	1.22	1.05
Agriculture	1.46	1.37	1.32	0.82	0.71	0.62	0.64	0.67	0.70
Industry	1.72	1.78	1.52	0.86	0.87	0.75	0.86	0.91	0.78
Services	2.69	2.80	2.45	1.15	1.31	1.18	1.54	1.48	1.27

Note. NCR = National Capital Region, HS = high school.

Table 3. *Percentage of Gap Explained by the Variables*

%Explained	UPPER 10th > LOWER 10th (90/10)			UPPER 10th > MID 10 (90/50)			MID 10 > LOWER 10th (50/10)		
	2007	2012	2017	2007	2012	2017	2007	2012	2017
Overall	6.4%***	1.2%	5.5%***	8%***	2.9%***	7%***	0.7%***	(−)0.1%	(−)0.2%
Male	4.6%***	2.7%**	8.3%***	10.7%***	5.7%***	10.7%***	(−)5.3%***	(−)1.3%**	(−)0.2%
Female	3.3%***	2.2%	1.2%	5.3%***	3.1%***	3.7%***	1.2%**	1.2%	(−)0.1%
NCR	6.4%***	1.8%	5.2%***	4.4%***	3.9%***	6.2%***	0.4%***	0.7%	1.2%
Non-NCR	6.1%***	2.8%**	2.8%***	5.7%***	2.9%***	5.1%***	1.3%***	0.7%	(−)1.5%
College grad	3.4%***	0.8%	2.7%***	2%***	0.7%	2.7%***	0.1%***	0.2%	(−)0.9%
HS grad	0.1%	(−)3%***	(−)2.2%***	(−)6.1%***	(−)3.6%***	(−)1.8%**	1.2%*	0.1%	1.4%*
Agriculture	2.8%**	(−)5.8%***	(−)2.4%	4.6%***	(−)3.5%	(−)7.7%***	(−)8.8%***	(−)18.6%***	(−)0.5%
Industry	10.4%***	9.1%***	8.8%***	19.1%***	16.1%***	13.9%***	(−)5.9%***	5.2%***	0%
Services	5.5%***	3.1%***	3.9%***	5.4%***	2.5%***	6.3%***	1.6%***	0.8%*	(−)0.2%

Note. A (−) before the percentage indicates a negative coefficient. NCR = National Capital Region, HS = high school.
***Highly statistically significant, below 1% level. **Significant at 5% level. *Significant at 10% level.

unaccounted for such as skills, years of experience, type of management, or years working in the industry.

Individual Contribution of Factor to Explained Portion

Next, we look at the individual contribution of the predictors, focusing more on *education*.[13] Results show that *education* and *location* tend to account for the large chunk of the *explained* component for each category under different wage gap groupings. For instance, for the female category, the huge portion of the 90/10 *explained* component is due to *location* and then followed by *education*. The inverse was observed for the 90/50 and 50/10 gap groupings and is seen in all gap groupings for the male category.

Table 4 shows the contribution as a percentage of the *explained* portion for each grouping. Recall that from Table 3, we have established that the percentage of the wage differential explained by the variables is small. Hence, we interpret the table with caution as the percentage of *explained*, especially for the 90/10, 90/50, and 50/10 gaps, is quite small—thus, the actual

Table 4. *Percentage of the Explained Accounted for by EDUCATION*

% Education	UPPER 10th > LOWER 10th (90/10)			UPPER 10th > MID 10 (90/50)			MID 10 > LOWER 10th (50/10)		
	2007	2012	2017	2007	2012	2017	2007	2012	2017
Overall	42.6%***	14.5%	58.6%***	43.6%***	47.1%***	60%***	54%***	35%*	28.6%**
Male	55%***	42.6%***	80.3%***	62.1%***	61.4%***	87.2%***	9.6%**	8.3%	30.3%***
Female	34.4%	22.2%	(−)10.9%	63.2%***	43.6%***	36.1%***	76.8%***	39.4%**	(−)29.7%
NCR	77.7%***	47.3%	81.3%***	71.5%***	48.2%**	67.5%***	26%***	32.2%	56.9%
Non-NCR	56.1%***	43.9%*	61.5%***	61.1%***	38.9%***	61.6%***	24.7%***	0.8%	10.9%
Agriculture	47.6%***	5%	19.7%	59.3%***	24.4%***	20.5%***	(−)3.9%***	(−)3.1%	26%
Industry	65.6%***	75.6%***	63.8%***	86.5%***	86.7%***	72%***	1.7%***	11.2%**	39.4%***
Services	45.3%***	34%	48.6%**	58%***	35.4%***	42.6%***	25.2%**	17.7%	35.6%

Note. A (−) before the percentage indicates a negative coefficient. NCR = National Capital Region.
****Highly statistically significant, below 1% level. **Significant at 5% level. *Significant at 10% level.*

contribution of *education* is even smaller. For instance, the values of the 50/10 gap grouping for the overall category in 2007 from both Table 3 and Table 4 are 0.7% and 54%, respectively. This means that only 0.7% of the wage differential is collectively explained by the variables included in the study, which is minimal or even negligible. This highly suggests the need to consider other factors. The 54% which indicates the contribution of the *education* variable to the *explained* portion might seem high, but note that this is 54% of the 0.7%, which is rather small.

We mainly focus on *education* since it accounts for the large fraction of the *explained* component of the wage gap models, except for the 50/10 gap. A positive percentage indicates that the mean coefficient for education is also positive, implying that this component contributes to the mean increase in the wage gap. A negative percentage indicates that *education* has negative influence on the wage differential, which tells us that this predictor decreases the wage gap. Although statistically insignificant, this is observed among female workers in the 90/10 and 50/10 wage gap groupings for the year 2017. In general, the statistically significant values found in Table 4 imply that *education* has an upward influence on the wage differentials between the identified gap groupings for the various categories.

For the 90/10 and 90/50 gap groupings, the contribution of *education* to the wage differentials is higher for male, NCR, and industry *sector* workers compared to their respective counterparts. For the 50/10 gap grouping, the opposite is observed for female and service *sector* workers. Generally, the same gap grouping exhibits lower percentages compared to the 90/10 and 90/50 gaps. This may be due to the low percentage of the estimated difference explained by the variables.

We also find that *location*, in general, constitutes a large part of the *explained* component of college and high school graduate categories, followed by *age* and *sector*.

Conclusions

Using the 2007 to 2017 October rounds of the Philippine LFS, we find that wage gap exists between different wage percentiles considering *gender*, *education*, *region*, and *sectors* as factors that can influence the changes in log wages.

We observe that the wage gaps are lower in 2017 than in 2007 for the 90/10 and 50/10, although there are increases during the years in between. Through the wage gap analysis and OBD methods, we notice that for the 90/10, 90/50, and 50/10 gaps, female workers experience a higher wage differential among themselves compared to male workers. Similarly, the highest wage gap is observed in the service *sector*, followed by the industry *sector.* Meanwhile for *location*, workers in non-NCR are reported to have higher wage differential relative to workers in NCR for the 90/10 and 90/50 gaps.

In addition, both methods show that for the 90/10 and 50/10 gaps, wage differences between workers categorized into *gender*, *location, education*, and *sector* have decreased from 2007 to 2017. However, for college graduates, the wage differential is observed to have increased.

OBD results show that *education* generally has an upward impact on the inequalities between the different gap groupings for the different categories and has the highest influence relative to other variables. However, it important to emphasize that if we consider the portion explained by the model, the impact of *education* is quite small, implying the need to account for other variables such as skills, experience, policies, and type of management.

In this study, we are aware of some considerations that need to be made. First, we are not able to consider years prior to 2007 due to the inconsistencies in the information available from the previous LFS survey. Second, we are not able to account for experience since *education* in LFS is merely in terms of highest educational attainment and not the years of schooling, preventing us from constructing the Mincerian method of potential labor market experience. Hence, for future research, it would be useful to find a measure for work experience and use it as a factor for changes in wage inequality.

Notes

[1]All wages refer to real wage rates.

[2] See Chow, Dabbay, and Sauler (2019) for additional trends identified, including daily log wage. The changes in the average wages were calculated by normalizing the average wages for the 90th, 50th, and 10th percentiles to 100.

[3] Sakellariou (2012) considers the entire Metropolitan Manila area, which also refers to the National Capital Region (NCR).

[4] Tables and graphs for the basic data are available upon request from the author.

[5] PSA serves as the central statistical authority of the Philippine Government. It is brought about by the merging of the National Statistics Office (NSO), National Statistical Coordination Board (NSCB), Bureau of Labor and Employment Statistics (BLES), and Bureau of Agricultural Statistics in 2014. This is due to the Philippine Statistical Act of 2013, signed by then President Benigno S. Aquino III, which took effect on December 29, 2013.

[6] Gender dummy: female; education dummies: elementary undergraduate, elementary graduate, high school undergraduate, high school graduate, college undergraduate, and college graduate; location (region) dummies: 16 regions; sector dummies: industry and services.

[7] Another way to express the decomposition would be

$$\hat{\bar{y}}_t - \hat{\bar{y}}_b = \Delta x \hat{\beta}_b + \Delta\beta \hat{x}_t$$

Here the differences in the xs are weighted by the coefficients of the lower tail group and the differences in the coefficients are weighted by the xs of the upper tail group. Either of the two methods can be used.

[8] We take note of interesting findings based on these methods. Additional analyses are done based on all categories but may not be included in this paper. The authors may be contacted for any questions.

[9] "Wage gap groupings" shall be the term used to jointly refer to 90/10, 90/50, and 50/10 wage gaps.

[10] Readers interested in the graph may request it from the authors.

[11] The results of Oaxaca–Blinder decomposition per group can be provided by the authors upon request.

[12] The numbers 90/10, 90/50, and 50/10 shall pertain to upper 10th and lower 10th, upper 10th and middle 10th, and middle 10th and lower 10th, respectively.

[13] We look at education given its size compared to the other variables in terms of percentage to the explained part of the model, even though the explained part by itself is small for the 90/10, 90/50, and 50/10 gap groupings. The result for the other variables can be provided by the authors upon request.

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