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The Effects of Distributional Assumptions on the Full-time and Part-time Wage Differentials

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Abstract

The extent to which the distribution of the disturbance term in the estimated wage equation affects the wage differential between full-time and part-time workers is examined in this paper. Adopting a switching regression model with known sample selection, I found that the normality assumption generates larger wage estimates than the estimates of the non-normal distributions. The results indicate that the Normal distribution produces the larger wage differentials than the Non-normal distributions. Also, regardless of distributional assumption, differences in full-time and part-time characteristics account for a larger portion of the full-time and part-time wage differentials. The empirical message derived from this study is that, studies that rely solely on the normality assumption may not provide a true picture of the size of the estimated wage gap between full-time and part-time workers. In general, the study seems to suggest that the estimated wage differential between groups such as male-female and white-black under the normality assumption may be overstated.

JEL classification numbers: J31, J22, J23, J20.
Keywords: Distributional assumptions, Switching regression, Normal and Non-Normal distributions, Full-time/Part-time wage differentials.

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1. Introduction

The past two decades have witnessed a great deal of research on full-time and part-time wage differentials. Most of these studies demonstrate that full-time workers enjoy a sizeable advantage over part-time workers across industries and occupations. Such wage differences have been attributed to a variety of factors. Hirsch (2005) concluded that the worker-specific skills and occupational skills accounted for large differences in wages between part-time and full-time workers. Baffoe-Bonnie (2004) estimated that about 10 percent of the wage differential is attributed to differences in human capital acquisition of the two groups.

The most common theoretical explanation of the wage differential stems from the fact that labor generates quasi-fixed cost (Oi, 1962; Montgomery, 1988; Hamermesh and Reese, 1993). The presence of quasi-fixed hiring and training costs that are more likely related to the number of employees rather than their total hours worked encourages firms to offer higher wage rates for longer hours workers per employee (Pencavel, 1986). Another explanation is related to the differences in the productivity of the two groups that engage in the same job. It is argued that in jobs where workers acquire on-the-job training, full-time workers are likely to be more experienced and therefore more productive than part-time workers given that both groups have the same formal education or credentials (Blank, 1998), (Hirsch, 2005) and (Manning and Petrognolo, 2008).

While the existence of full-time and part-time wage differential is a well-established fact, the size of the differential is an empirical issue.[1] The models used to estimate the wage equation typically assume that either the observations themselves or the random errors in the model are normally distributed. However, studies indicate that the parameter estimates are sensitive to distributional assumptions that underlie the model (Goldberger, 1983; Bera et. al., 1984). The argument is that different distributions of the disturbance term may lead to different estimates and therefore different wage differentials between full-time and part-time workers (Vijverberg, 1987; Baffoe-Bonnie and Gyapong 2018).

This paper focuses on two related questions: (1) Is there more evidence that the wage equation parameters are sensitive to the distributional assumptions about the error term? and (2) To what extent do different distributions about the error term affect the full-time and part-time wage differentials? These questions are addressed by estimating a switching regression model based on the assumption that the error terms in the model have Normal, Weibull, and Exponential distributions. Using the Current Population Survey (CPS) data set, the likelihood functions associated with each of the distributions are estimated with a Maximum likelihood technique. In section 2, I present the motivation or the background of the study, followed by section 3 that describes the empirical model and the method used to estimate the wage differential between the full-time and part-time workers. The description of the data source and the variables used in the study are presented in section 4. The next section presents the estimation procedure, the discussion of the results, and test results, while the last section presents the summary and conclusions.

2. Motivation

There are two issues addressed in this paper.[2] First, the normality assumption of the disturbance term may not be appropriate in (i) censored and truncation models, (ii) when the observations are non-normal, and (iii) when the disturbance term is not normally distributed. The justification of studies assuming a Normal distribution of the disturbance term in regressions rests on the central limit theorem which states that if the size of the sample (n) is large, the theoretical sampling distribution of the mean of the variables ($\bar{X}$) will be close to a Normal distribution regardless of the shape of the distribution of the basic population. In regression models, the effect of the excluded independent variables are captured by the disturbance term, and assumed to have a normal distribution.

Also, the values of the disturbance term of the independent variables have a common distribution (a bell-shaped symmetrical distribution) about their zero mean. The empirical skeptics of the models based on normality assumption argue that the different assumptions of the disturbance lead to different estimates (Goldberger (1983); Bera et al. (1984); Vijverberg (1987)). Vijverberg showed that the labor supply estimates depend heavily on the distribution used and concluded that in a labor supply model of married males, the wage elasticities tend to be overestimated when one uses the Normal distribution (Vijverberg, 1991, p. 835). It has also been demonstrated that if the underlying disturbances are not normally distributed, as in the case of censored and truncated data, the estimated coefficients may be inconsistent (Anderson (1982); Hay (1980); Olsen (1982). In light of these findings, some researchers have resorted to a use of alternative distributions such as the Weibull and Exponential distributions (Kalbfleisch and Prentice, (2002), and different estimation procedures, Chay and Honore (1988).

With this background, one should question whether the disturbance term in the wage equation could be non-normal. In fact, the inclusion of discrete variables such as regional variables, race, marital status, and health conditions that reflect socioeconomic, regional and family background of individuals in a sample could create a non-normal disturbance term in the wage equation (Polachek and Yoon (1987).[3] There are different normality tests of the error term. An informal approach to testing normality is to compare a histogram, normal Q-Q plots, and box plots of the sample data to a normal probability curve. The empirical distribution of the data should be bell-shaped and resemble the Normal distribution if the sample is large. Another approach is to use a statistical test of normality such as the skewness and kurtosis of the data, the Shapiro-Wilk and Kolmogorov-Smirmov tests of normality. In Table 1, the Shapiro-WilK's and Kolmogorov-Smirmov tests and the visual inspection of histogram normal Q-Q plots and box plots showed that the wage variableis not approximately normally distributed.[4]

Table 1: Test of Normality of the Wage Variable for Full-Time and Part-Time Samples

	Kolmogorov-Smirnov			Shapiro-Wilk			Skewness		Kurtosis	
	Statistic	df	Sig	Statistic	df	Sig	Statistic	SE	Statistic	SE
Full-Time Sample	0.087	2071	<0.001	0.868	2071	<0.001	0.238	0.039	0.875	0.073
Part-Time Sample	0.053	1389	<0.001	0.094	1389	<0.001	0.231	0.040	0.636	0.058

Note: The null hypothesis (H0) of the Shapiro-Wilk and Kolmogorov-Smirnov tests is that the dependent variable (Wage) is approximately normally distributed. It is rejected when the p-value(sig) is less than (0.05). The calculated Skewness and Kurtosis values (Statistic value/SE) should lie outside the Z-values of (-1.96 and + 1.96).

I also checked for the best distribution that represents the wage data. Different tests provided by the ExpertFit software were used to determine the best distribution for the data. The ExpertFit software allows a researcher to determine automatically and accurately which probability distribution best represents a data set. Different tests such as goodness of fit based on the Anderson-Darling test, probability plots using relative discrepancies, and log-likelihood test, all ranked the Weibull as the best, followed by the normal and the exponential distributions.[5]

Second, the extent to which different distributions in the disturbance term may produce different estimates in the wage equation has not received much attention in the wage differentials literature. This study seeks to answer an important question: are the wage differentials between full-time and part-time workers sensitive to the distributional assumptions against the backdrop that the disturbance term in the wage equation in selectivity models may not be normally distributed?

3. The Endogenous Switching Regression with Known Sample Selection Model

The switching regression model is written as:

$$lnw_{fi} = x_i\theta_f + \upsilon_{fi} \quad if \quad h_i \geq h^* \tag{1}$$

$$lnw_{pi} = x_i\theta_p + \upsilon_{pi} \quad if \quad 0 < h_i < h^* \tag{2}$$

$$h_i = z_i\pi + \epsilon_i, \tag{3}$$

where equations (1) and (2) are the wage equations for the full-time and part-time workers, respectively, and equation (3) determines the tendency for an individual to be in the full-time or part-time employment. lnw_i is the natural log of the hourly wage rate of individual i; x_i and z_i are vector of exogenous variables, where $z_i = [(lnw_{fi} - lnw_{pi})\psi + \mu] + \beta y_i$, and y_i is vector of other variables that affect the hours of work equation. The θs, ϕs,

πs, μ and β are vectors of parameters, $\upsilon_{fi}, \upsilon_{pi}$, and $\epsilon_i = (\upsilon_{fi} - \upsilon_{pi})\psi + \mu$ are disturbance terms. The h_i is observable hours of work of an individual i and h^* is the level of hours of work that determines whether an individual is a full-timer or a part-timer. It is the latent variable or a switch parameter that determines the tendency to be in full-time or part-time employment. In this model, the sorting or switch equation (3) depends on the difference between full-time and part-time wages and the characteristics of the worker.

Assuming a joint multinormal distribution, the conditional distribution of the disturbance terms in equations (1)-(3) for the entire population is given by $(\upsilon_{fi}, \upsilon_{pi}, \epsilon_i \sim N(0, \Sigma)$, and the variance-covariance matrix of the disturbance terms is:

$$\Sigma = Cov(\epsilon, \upsilon_f, \upsilon_p) = \begin{bmatrix} \sigma_f^2 & \rho_{fp} & \rho_{f\epsilon} \\ \rho_{pf} & \sigma_p^2 & \rho_{p\epsilon} \\ \rho_{\epsilon f} & \rho_{\epsilon p} & \sigma_\epsilon^2 \end{bmatrix}$$

There are three different workers in the switching regression model: (i) individuals who are not employed and therefore their hours of work are zero (i.e., $h_i \leq 0$), (ii) full-time workers (i.e., $h_i \geq h^*$), and (iii) part-time workers (i.e., $0 < h_i < h^*$). To derive a likelihood function for equations (1)-(3) that incorporates these three categories of workers, we define two dummy variables as follows:

$$k_1 = \begin{cases} 1, & \text{if employed} \\ 0, & \text{if unemployed} \end{cases} \tag{4}$$

and

$$k_2 = \begin{cases} 1, & \text{if full-time worker} \\ 0, & \text{if part-time worker} \end{cases} \tag{5}$$

k_1 and k_2 are the indicator variables that define the labor market status of individuals: (i) If an individual is not working or unemployed, (i.e., $h_i \leq 0$), $k_1 = 0$); (ii) If an individual is a full-time worker, ($k_1 = 1$ and $k_2 = 1$); and (iii) If an individual is a part-time worker,

($k_1 = 1$ and $k_2 = 0$). Given the indicators k_1 and k_2, we can specify the likelihood functions of the three categories for each distribution considered in the paper.

3.1 Normal Distribution

The likelihood function obtained from considering the joint density of h_i and lnw_i for the Normal distribution is given by:[6]

$$L_i = \left\{ \left[\frac{f_f(lnw_{fi}, h_i)}{1 - \Phi\left(\frac{h^* - Z_i\pi}{\sigma_\epsilon}\right)} \right]^{k_2} \left[\frac{f_p(lnw_{pi}, h_i)}{\Phi\left(\frac{h^* - Z_i\pi)}{\sigma_\epsilon}\right) + \Phi\left(\frac{z_i\pi}{\sigma_\epsilon}\right) - 1} \right]^{1-k_2} \right\}^{k_1}$$

$$\times \quad \left[1 - \Phi\left(\frac{Z_i\pi}{\sigma_\epsilon}\right) \right]^{1-k_1} \tag{6}$$

where $f_f(.,.)$ and $f_p(.,.)$ represent bivariate normal probability distribution functions for full-time and part-time workers , and Φ is the normal cumulative distribution function.

3.2 Weibull Distribution

In order to derive a Weibull likelihood equivalent of equation (6), we adopt a bivariate Weibull distribution derived from two Weibull marginals with two parameters.[7] Each marginal distribution has a shape parameter c_i, a scale parameter b_i and a non-negative correlation δ between the two components or marginals (also known as a mixing parameter). The probability density function for this bivariate Weibull is given by:[8]

$$\frac{c_1}{b_1}\left(\frac{lnw}{b_1}\right)^{\left(\frac{c_1}{\delta}\right)^{-1}} \left(\frac{c_2}{b_2}\right)\left(\frac{h}{b_2}\right)^{\left(\frac{c_2}{\delta}\right)^{-1}} \left\{ \left(\frac{lnw}{b_1}\right)^{\frac{c_1}{\delta}} + \left(\frac{h}{b_2}\right)^{\frac{c_2}{\delta}} \right\}^{\delta-2}$$

$$\times \left\{ \left[\left(\frac{lnw}{b_1}\right)^{\frac{c_1}{\delta}} + \left(\frac{h}{b_2}\right)^{\frac{c_2}{\delta}} \right]^{\delta} + \frac{1}{\delta} - 1 \right\}$$

$$\times \exp\left\{-\left[\left(\frac{lnw}{b_1}\right)^{\frac{c_1}{\delta}}+\left(\frac{h}{b_2}\right)^{\frac{c_2}{\delta}}\right]^{\delta}\right\} \quad 0<\delta\leq 1$$

The Weibull equivalent of $f_f(lnw_{fi}, h_i)$ in equation (6) is given by:

$$\frac{c_{1f}}{b_{1f}}\left(\frac{lnw_f}{b_{1f}}\right)^{\left(\frac{c_{1f}}{\delta}\right)^{-1}}\left(\frac{c_{2f}}{b_{2f}}\right)\left(\frac{h_i}{b_{2f}}\right)^{\left(\frac{c_{2f}}{\delta}\right)^{-1}}\left[\left(\frac{lnw_f}{b_{1f}}\right)^{\frac{c_{1f}}{\delta}}+\left(\frac{h_i}{b_{2f}}\right)^{\frac{c_{2f}}{\delta}}\right]^{\delta-2}$$

$$\times\left\{\left[\left(\frac{lnw_f}{b_{1f}}\right)^{\frac{c_{1f}}{\delta}}+\left(\frac{h_i}{b_{2f}}\right)^{\frac{c_{2f}}{\delta}}\right]^{\delta}+\frac{1}{\delta}-1\right\}$$

$$\times \exp\left\{-\left[\left(\frac{lnw_f}{b_{1f}}\right)^{\frac{c_{1f}}{\delta}}+\left(\frac{h_i}{b_{2f}}\right)^{\frac{c_{2f}}{\delta}}\right]^{\delta}\right\} \qquad 0<\delta\leq 1 \qquad (A_i)$$

And $f_p(lnw_{pi}, h_i)$ is given by:

$$\frac{c_{1p}}{b_{1p}}\left(\frac{lnw_p}{b_{1p}}\right)^{\left(\frac{c_{1p}}{\delta}\right)^{-1}}\left(\frac{c_{2p}}{b_{2p}}\right)\left(\frac{h_i}{b_{2p}}\right)^{\left(\frac{c_{2p}}{\delta}\right)^{-1}}\left[\left(\frac{lnw_p}{b_{1p}}\right)^{\frac{c_{1p}}{\delta}}+\left(\frac{h_i}{b_{2p}}\right)^{\frac{c_{2p}}{\delta}}\right]^{\delta-2}$$

$$\times\left\{\left[\left(\frac{lnw_p}{b_{1p}}\right)^{\frac{c_{1p}}{\delta}}+\left(\frac{h_i}{b_{2p}}\right)^{\frac{c_{2p}}{\delta}}\right]^{\delta}+\frac{1}{\delta}-1\right\}$$

$$\times \exp\left\{-\left[\left(\frac{lnw_p}{b_{1p}}\right)^{\frac{c_{1p}}{\delta}}+\left(\frac{h_i}{b_{2p}}\right)^{\frac{c_{2p}}{\delta}}\right]^{\delta}\right\} \qquad 0<\delta\leq 1 \qquad (B_i)$$

The cdf for the Weibull distribution for the expressions in the denominator of equation (6) is given by:

$$1-\exp\left(-\frac{z_i\pi}{b_i\sigma_\epsilon}\right)^{c} \qquad (C_i)$$

$$1 - \exp\left(-\frac{h^* - z_i\pi}{b_i\sigma_\epsilon}\right)^c \tag{D_i}$$

The likelihood function of the bivariate Weibull distribution equivalence of equation (6) can therefore be written as:

$$L_i = \left[\left(\frac{Ai}{D_i}\right)^{d_2}\left(\frac{B_i}{1 - D_i + C_i - 1}\right)^{1-d_2}\right]^{d_1} \times (C_i)^{1-d_1} \tag{7}$$

3.3 Exponential Distribution

Setting $c = 1$ in equations (A_i) to (D_i) gives the likelihood function of the Exponential distribution for equation (6).

$$\frac{1}{b_{1f}}\left(\frac{lnw_f}{b_{1f}}\right)^{\left(\frac{1}{\delta}\right)^{-1}}\left(\frac{1}{b_{2f}}\right)\left(\frac{h_i}{b_{2f}}\right)^{\left(\frac{1}{\delta}\right)^{-1}}\left[\left(\frac{lnw_f}{b_{1f}}\right)^{\frac{1}{\delta}} + \left(\frac{h_i}{b_{2f}}\right)^{\frac{1}{\delta}}\right]^{\delta-2}$$
$$\times\left\{\left[\left(\frac{lnw_f}{b_{1f}}\right)^{\frac{1}{\delta}} + \left(\frac{h_i}{b_{2f}}\right)^{\frac{1}{\delta}}\right]^{\delta} + \frac{1}{\delta} - 1\right\}$$
$$\times\exp\left\{-\left[\left(\frac{lnw_f}{b_{1f}}\right)^{\frac{1}{\delta}} + \left(\frac{h_i}{b_{2f}}\right)^{\frac{1}{\delta}}\right]^{\delta}\right\} \qquad 0 < \delta \le 1 \tag{E_i}$$

And $f_p(lnw_p, h_i)$ is given by:

$$\frac{1}{b_{1p}}\left(\frac{lnw_p}{b_{1p}}\right)^{\left(\frac{1}{\delta}\right)^{-1}}\left(\frac{1}{b_{2p}}\right)\left(\frac{h_i}{b_{2p}}\right)^{\left(\frac{1}{\delta}\right)^{-1}}\left[\left(\frac{lnw_p}{b_{1p}}\right)^{\frac{1}{\delta}} + \left(\frac{h_i}{b_{2p}}\right)^{\frac{1}{\delta}}\right]^{\delta-2}$$
$$\times\left\{\left[\left(\frac{lnw_p}{b_{1p}}\right)^{\frac{1}{\delta}} + \left(\frac{h_i}{b_{2p}}\right)^{\frac{1}{\delta}}\right]^{\delta} + \frac{1}{\delta} - 1\right\}$$
$$\times\exp\left\{-\left[\left(\frac{lnw_p}{b_{1p}}\right)^{\frac{1}{\delta}} + \left(\frac{h_i}{b_{2p}}\right)^{\frac{1}{\delta}}\right]^{\delta}\right\} \qquad 0 < \delta \le 1 \tag{F_i}$$

And the expressions in the denominator of equation (6) for the Exponential distribution are given by:

$$1 - \exp\left(-\frac{z_i \pi}{b_i \sigma_\epsilon}\right) \tag{G_i}$$

$$1 - \exp\left(-\frac{h^* - z_i \pi}{b_i \sigma_\epsilon}\right) \tag{H_i}$$

The likelihood function of the bivariate Exponential distribution equivalent of equation (6) can be written as:

$$L_i = \left[\left(\frac{Ei}{H_i}\right)^{d_2}\left(\frac{F_i}{1 - H_i + G_i - 1}\right)^{1-d_2}\right]^{d_1} \times (G_i)^{1-d_1} \tag{8}$$

$$L_i = \left\{\left[\frac{f_f(lnw_{fi}, h_i)}{1 - \Phi\left(\frac{h^* - Z_i\pi}{\sigma_\epsilon}\right)}\right]^{k_2}\left[\frac{f_p(lnw_{pi}, h_i)}{\Phi\left(\frac{h^* - Z_i\pi)}{\sigma_\epsilon}\right) + \Phi\left(\frac{z_i\pi}{\sigma_\epsilon}\right) - 1}\right]^{1-k_2}\right\}^{k_1}$$

$$\times \quad \left[1 - \Phi\left(\frac{Z_i\pi}{\sigma_\epsilon}\right)\right]^{1-k_1} \tag{9}$$

3.4 Decomposition of the Full-time and Part-time Wage Differentials

In linear regression models, the Blinder-Oaxaca decomposition method is widely used to decompose wages into different components: (1) a portion due to differences in average personal characteristics, and other variables in the wage equation, and (2) a portion due to differences in the parameters of the wage function, caused by labor market discrimination and other omitted factors.

The standard Blinder (1973) and Oaxaca (1973) linear regression decomposition of full-time (f) and part-time (p) wage differential is given by:

$$\bar{W}^f - \bar{W}^p = \left[\sum_{i=1}^{N^j} (\bar{X}_i^f - \bar{X}_i^p)\hat{\beta}^f\right] + \left[\sum_{i=1}^{N^j} \bar{X}_i^p(\hat{\beta}^f - \hat{\beta}^p)\right] \quad (10)$$

where N^j is the sample size for the j worker, $(j = f, p)$, $\bar{X}_i$ is a row vector of average values of the independent variables, β^j is a vector of coefficient estimates for the full-time and part-time workers, and W^f and W^p are the wage of the full-time and part-time workers, respectively, and N is the sample size. Following Fairlie (1999), the nonlinear decomposition for the above equation is given by:

$$\bar{W}^f - \bar{W}^p = \left[\sum_{i=1}^{N^f} \frac{F(X_i^f\hat{\beta}^f)}{N^f} - \sum_{i=1}^{N^p} \frac{F(X_i^p\hat{\beta}^f)}{N^p}\right] + \left[\sum_{i=1}^{N^p} \frac{F(X_i^p\hat{\beta}^f)}{N^p} - \sum_{i=1}^{N^p} \frac{F(X_i^p\hat{\beta}^p)}{N^p}\right] \quad (11)$$

where F is a specific distribution function (in this case, Normal, Weibull and Exponential or the cumulative distribution function from Weibull and Exponential distributions). The $(\hat{\beta}^f)$ and $(\hat{\beta}^p)$ are coefficient estimates of the full-time and part-time wage equations, respectively. With this non-linear decomposition approach, $\bar{W}$ does not necessary equal to $F(\bar{X}\hat{\beta})$ (Fairlie, 2005). The N^f, and N^p are the sample size for the full-timers and part-timers, respectively. The first term on the right-hand side of equation (11) is the difference in the endowments of wage-determining characteristics $(X's)$ between the full-time and part-time workers. This portion can also be interpreted as the wage gain part-timers would experience if they had the same characteristics, on average, as full-timers. The second term on the right-hand side is the portion due to differences in pay structure (coefficients, β's) between full-timers and part-timers. It is the wage gain part-timers would experience, given their mean characteristics, if they were remunerated like full-timers.[9]

Equation (11) suffers the familiar Blinder-Oaxaca decomposition index problem. If the estimates of the part-timers coefficients $(\hat{\beta}^p)$ are used as weights for the first term on the right side and the full-timers' distributions of the independent variables, $(\bar{X}^f)$ are used as weights in the second term, the decomposition approach as stated in equation (11) will produce different decomposition results. In light of this index problem, I adopted Fairlie,(1999, 2005); Neumark (1988) and Oaxaca and Ransom (1994) approach by using the coefficient estimates from the pooled sample of the full-time and part-time workers as weights in the first term of Equation (11). Also, Fairlie (2017) addressed the potential concern that the technique of the non-linear decomposition results may depend on the ordering of variables in model.[10]

4. Data Source, Sample Selection, and Variable Description

The data set used for this study comes from the March 2022 Supplement of the Current Population Survey (CPS). The CPS data provides a wide variety of variables on economic status and activities of the population of the United States, including demographic and labor force data on heads of household, family members, and individuals (persons) in a household. The March supplement data, also known as Annual Social and Economic (ASEC) data set and until 2003 formerly known as Annual Demographic File (ADF), is the most widely used type of CPS data because of its rich information on all demographic and labor force variables, plus additional data on work experience, income, non-cash benefits, and migration. A detailed description of the ASEC data set can be found in The CPS-March Supplement User Guide.

The sample consists of heads of household, who are salaried workers with only one job. I excluded all self-employed workers, and those who worked part-time because of health problems or inability to find jobs. This selection criteria was to ensure that individuals working part-time were purely voluntary. To ensure that the working population is consistent with the definition of United States of America (USA) labor, the age was constrained to be greater than 15 years. It has been documented that the standard full-time work of 35 hours per week or more and less than 35 hours per week for part-time workers has important impact on the estimated hourly earnings function (Ermisch and Wright 1993; Hotchkiss, 1989, 1991; Baffoe-Bonnie and Gyapong 2018). Hotchkiss provided empirical results that suggested that the standard 35 hours per week definition used in United States is too low. Baffoe-Bonnie and Gyapong (2018) using the same methodology estimated hours of work cut off points that differ according to the distributional assumption imposed on the error term in the wage equation. In this paper, I use the standard definition specified by CPS. That is, full-timers are workers who work 35 or more hours per week (that is, $h^* \geq 35$) and part-timers are those who work less than 35 hours per week ($h^* < 35$). Using a sample based on this definition will enable me to compare the wage differential studies that employ the standard definition with the results in this paper.

The variables included in the wage equations are defined as follows:

1. Edu is the highest grade of school completed.
2. Age is the age of the head of household.
3. Agesq is age squared.
4. Exp is labor market experience (AGE x EDU) in 100 years. The CPS data do not have a true measure for experience. The (AGE-EDU-5) often used as a proxy for experience has been noted to be a notoriously poor measure, especially for women. Instead, we adopt (AGE x EDU) suggested by Blinder for experience. For a discussion of the experience variable, see Blinder (1976) and Rosenzweig (1976).
5. Expsq is experience squared in 100's.
6. Female equal to 1 if head is female and 0 if otherwise.
7. Black equal 1 if head is black and 0 if white.
8. Public equal to 1 if head is employed in public sector (federal, state or local) and 0 otherwise.

9. Health equal to 1 if head has a problem or disability that prevents him/her from working and 0 otherwise.
10. Single equal 1 if head is unmarried and 0 otherwise.
11. Union equal to 1 if a worker is a member of union and 0 otherwise.
12. South equal to 1 if head is located in South and 0 if located in the Northeast.
13. West equal to 1 if head is located in West and 0 if located in the Northeast.
14. Midwest equal to 1 if head is located in Midwest and 0 if located in the Northeast.
16. Wage (W) is the hourly wage of the head of household's main job.
17. Number of children under 18 years.
18. Family size.
19. Other family income.

The variables in the hours of work or labor force participation equation (3) include all variables in the wage equation except public and union variables. It also includes the number of children under 18 years, family size, and other income of the family. Table 2 presents the descriptive statistics of the variables for the full-time and part-time workers. Since I am interested in the wage equation, I did not include the descriptive statistics of variables 17-19 in Table 2.

5. Estimation procedure and Results of the Wage Equations

This section reports the estimation procedure and results. Equations (6), (7) and (9) were estimated simultaneously assuming different distributions of the error terms and using a maximum likelihood procedure. Specifically, I assumed three distributions–Normal, Weibull, and Exponential. In order to find the optimum of the likelihood functions, a package (MAXFUN) of numerical optimization algorithms is used for the models: Equations (6), (7) and (9) for the full-time and part-time workers.

Table 2: Descriptive statistics for variables. Mean and standard deviations (in brackets)

	Full-time	**Part-time**
Education (Edu)	17.56 (2.08)	9.23 (3.14)
Experience (Exp) (100)	14.87 (3.24)	2.98 (2.89)
(Expsq)(100)	38.61 (5.98)	8.88 (1.06)
Age	46.8 (4.33)	30.45 (3.65)
Agesq (100)	11.98 (3.06)	10.43 (2.87)
Health=1	0.0001 (0.07)	0.001 (0.01)
Single=1	0.002 (0.39)	0.0021 (0.77)
Black=1	0.002 (0.21)	0.012 (0.08)
Union=1	0.778 (0.55)	0.0005 (0.001)
Public=1	0.015 (0.35)	0.021 (0.03)
Female=1	0.449 (0.86)	0.112 (0.11)
South=1	0.141 (0.54)	0.281 (0.18)
West=1	0.659 (0.27)	0.125 (0.17)
Midwest=1	0.228 (0.21)	0.218 (0.13)
Wage	13.86 (0.18)	11.97 (0.09)
Sample size (N)	2071	1389

MAXFUN is a subroutine package for function maximization written by Sorant and Elston (1989) of the Department of Biometry and Genetics, Louisiana State University. Because no single method of nu- merical optimization is best for all situations, MAXFUN allows for the use of six different methods: two direct search methods, two Newton-Raphson methods, and two variable metric methods. The MAXFUN also allows us to search for the optimum estimates both locally and globally.

For the Weibull and the Exponential distributions, different starting values for the location (b_i) and shape (c_i) parameters were experimented with in order to achieve convergence. In the Weibull distribution, we constrained the shape parameter to be greater than unity to ensure that the likelihood function is bounded. The value of c, the shape parameter, is an important parameter and often has a characteristic or predictable value depending upon the fundamental nature of the problem being studied. It has been shown that if either b or c is assumed known, the maximum likelihood estimates of the remaining parameters always exist and are unique (Rockette et. al., 1974). When all the parameters are unknown, the likelihood function is unbounded as $b \rightarrow minx$. However, if one assumes $c \geq 1$, the likelihood function is bounded and often has a maximum. Convergence was achieved quicker in the Non-Normal distributions than the Normal distribution.[11] Table 3 presents the maximum likelihood estimates of equations (6), (7) and (9).

In accordance with the human capital theory, education and experience have a positive and significant impact on hourly wages for full-time and part-time workers for all distributions. The impacts of these variables are greater for full-timers than part-timers (Table 3). The smaller coefficients of the age variable in the part-time wage equation for all distributions suggest a flatter wage-age profile for part-time workers. For all distributions, full-time and part-time workers with ill-health face lower hourly wages.

Table 3: Maximum Likelihood Estimates of the wage Equations (6,7 & 9). Dependent variable is Log wage

	Normal		Weibull		Exponential		Pooled Sample*		
	FT	PT	FT	PT	FT	PT	Normal	Weibull	Exponential
Constant	2.5162	0.5616	0.8921	0.2452	0.6321	0.5281	0.6113	0.4962	0.4094
	(3.662)[a]	(1.798)[c]	(1.664)[c]	(1.648)[c]	(1.982)[b]	(1.884)[c]	(2.152)[b]	(2.013)[b]	(1.964)[b]
Edu	0.5991	0.4978	0.3984	0.0264	0.0319	0.0194	0.0402	0.0274	0.0148
	(4.121)[a]	(1.996)[b]	(2.883)[a]	(1.756)[c]	(2.225)[b]	(2.123)[b]	(3.861)[a]	(2.953)[a]	(2.149)[b]
Exp	0.6720	0.3142	0.3752	0.0312	0.0123	0.0301	0.2160	0.0942	0.0635
	(2.115)[b]	(2.017)[b]	(1.973)[b]	(1.886)[c]	(1.912)[b]	(1.872)[c]	(2.114)[b]	(1.994)[b]	(3.162)[a]
Expsq	-0.0002	-0.0001	-0.0001	-0.0001	-0.0001	-0.0021	-0.0002	-0.0002	-0.0001
	(-1.235)	(-1.374)	(-1.701)[c]	(-1.622)	(-0.767)	(-1.214)	(-0.576)	(-1.007)	(-0.985)
Age	0.4598	0.5166	0.2368	0.0031	0.0132	0.0013	0.0437	0.0303	0.0267
	(1.987)[b]	(2.621)[a]	(1.865)[c]	(1.657)	(2.111)[b]	(1.574)	(2.864)[a]	(1.876)[c]	(1.683)[c]
Agesq	-0.0004	-0.0001	-0.0002	-0.0002	-0.0002	-0.0001	-0.0003	-0.0003	-0.0003
	(1.881)[c]	(-1.672)[c]	(-1.713)[c]	(-1.779)[c]	(-1.573)	(-1.624)	(-1.982)[b]	(-2.574)[a]	(-1.992)[b]
Health=1	-0.0003	-0.0321	-0.0002	-0.0002	-0.0001	-0.0001	-0.0588	-0.0370	-0.0216
	(-3.165)[a]	(-2.771)[a]	(-2.855)[a]	(-2.075)[b]	(-1.872)[c]	(-1.663)[c]	(-2.192)[a]	(-2.121)[b]	(-1.982)[b]
Single=1	0.6150	-0.0162	0.3277	-0.0002	0.1377	-0.0001	-0.0951	-0.0592	-0.0516
	(1.636)	(-0.083)	(1.045)	(-1.608)	(1.721)[c]	(-1.257)	(-1.467)	(-0.834)	(-1.528)
Black=1	-0.0302	-0.0089	-0.0211	-0.0002	-0.0127	-0.0002	-0.0667	-0.0349	-0.0208
	(-2.821)[a]	(-1.853)[c]	(-1.968)[b]	(-2.021)[b]	(-1.792)[c]	(-2.215)[b]	(-3.152)[a]	(-2.718)[a]	(-3.002)[a]
Union=1	0.6858	0.1582	0.4215	0.0003	0.2387	0.0003	0.0078	0.0062	0.0026
	(4.025)[a]	(2.589)[a]	(2.220)[b]	(1.992)[b]	(1.824)[c]	(1.952)[c]	(3.181)[a]	(2.051)[b]	(1.854)[c]
Public=1	-0.0031	-0.1031	-0.0011	-0.0002	-0.0107	-0.0051	-0.4413	-0.2145	-0.1912
	(-1.692)[c]	(-1.621)	(-1.713)[c]	(-1.032)	(-1.813)[c]	(-1.541)	(-0.985)	(-1.554)	(-1.324)
Female=1	0.4331	0.1975	0.3932	0.0661	0.0818	0.0412	0.0782	0.0533	0.0331
	(2.176)[b]	(1.775)[c]	(2.092)[b]	(1.824)[c]	(1.963)[b]	(1.756)[c]	(1.762)[c]	(2.215)[b]	(1.917)[c]
South=1	0.4593	-0.0054	-0.3746	-0.0032	-0.1394	-0.0031	-0.0251	-0.0167	-0.0038
	(-2.127)[b]	(-1.984)[b]	(-1.583)	(-1.783)[c]	(-1.114)	(-1.782)[c]	(-1.573)	(-2.138)[b]	(-2.143)[b]
West =1	0.5256	0.3184	0.4416	0.0020	0.0384	0.0152	0.3961	0.2156	0.1692
	(1.896)[c]	(2.157)[b]	(1.692)[c]	(2.012)[b]	(1.691)[c]	(2.152)[b]	(1.941)[c]	(2.193)[b]	(1.885)[c]
Midwest=1	0.2856	0.0312	-0.2319	-0.0311	-0.1366	-0.0219	-0.0173	-0.0110	-0.0036
	(-0.967)	(-1.573)	(-1.441)	(-1.617)	(-1.825)[c]	(-0.927)	(-1.117)	(-1.412)	(-1.186)
sigma	0.218	0.185	0.214	0.177	0.158	0.103	0.215	0.307	0.428
C1 (shape)	---	---	2.22	1.75	2.10	1.76	---	2.09	2.71
C2	---	---	1.16	1.13	2.06	1.33	---	3.06	2.11
B1	---	---	3.23	2.85	3.16	2.97	---	4.87	3.76
B2	---	---	3.78	3.12	2.57	2.08	---	5.12	4.67
delta	0.5	0.4	0.5	0.6	0.7	0.4	0.6	0.4	0.3
Log L	-1842	-1644	-1934	-1567	-1387	-1122	-2321	-2036	-1996
N	2071	1389	2071	1389	2071	1389	3450	3460	3460

t-scores in parentheses. a Significant at 1% level; b Significant at 5% level; c Significant at 10% level. *Pooled sample=FT + PT

The results also reveal that being black or being single (with exception of full-time workers) reduces full-time and part-time workers' wages for all distributions.

Union membership has the expected positive influence on wages in all distributions, with full-time workers experiencing the greatest impact.

The impact of working in the public sector on wages is negative in all distributions.

Surprisingly, being female has a positive impact on females' wages for those working full -time and part-time. This positive impact may be due to some government policies aimed at addressing gender discrimination in the labor market.

The results of the regional variables indicate that in all distributions, full-time and part-time workers in the South and Midwest (except in the normal distribution) are paid less than their counterparts in the Northeast. In contrast, full-time and part-time workers in the West are paid higher wages than those in the Northeast.

Turning our attention to the effect of the distributional assumption on the wage estimates, the results indicate that, in general, the Normal distribution coefficients are relatively larger than the Weibull and the Exponential distribution coefficients. This result is consistent with previous studies that showed that the normal distribution estimates are larger than non-normal distribution estimates (see, Vijverberg, 1991; Goldberger, 1983; and Bera et.al. 1984). This finding is particularly important because such differences in coefficients have a direct influence on the wage gap between full-time and part-time workers across distributions. For example, in Table 3, the differences between the full-time and part-time education estimates are 0.1013 (0.5991-0.4978), 0.3720 (0.3984-0.0264), and 0.0125 (0.0319-0.0194), for the Normal, Weibull and Exponential distributions, respectively.

5.1 Test results

Using Pesaran et al.'s (1985) test, I tested whether the parameter estimates of the full-time and part-time workers' wage equations differ. The test verifies simultaneously the equality of variances of error terms and the equality of sets of coefficients of two regressors.

The null hypothesis is stated as: $H_0 : \beta_i = \beta_j$ and $\sigma_i^2 = \sigma_j^2$ against the alternative hypothesis: $\beta_i \neq \beta_j$ and $\sigma_i^2 \neq \sigma_j^2$. The test statistic is given by:

$$F = [(V_{ij}^{'}V_{ij} - V_i^{'}V_i)/n_j]/(V_i^{'}V_i)/(n_i - k) \sim F(n_j, n_i - k)$$

where $V_{ij}^{'}V_{ij}$ is the estimated sum of squared residuals of the pooled sample of n_i and n_j. $V_i^{'}V_i$ is the estimated sum of squared residuals of the ith regression with sample size n_i, and k is the number of explanatory variables in the regression. In this case, $n_i = n_f, n_j = n_p$, and $n_{ij} = n_{fp}$. The subscripts, f and p refer to full-time and part-time, respectively. A basic assumption for this test is that the error term of the regression is distributed $N(0, \sigma^2)$.[12] In all samples wage equations, the null hypothesis was rejected either at 1 percent or 5 percent level of significance. To confirm these test results, we employ the likelihood ratio test and again the null hypothesis was rejected at 1 percent level of significance in the full-time and part-time with the χ^2 statistics ranging from a low of 133.1 for part-timers to a high of 203.4 for the full-timers.

5.2 Results for the Full-time and Part-time Wage Differentials

The question posed in this paper is the extent to which distributional assumptions made about the error term in the wage equations affect the full-time and part-time workers wage differentials. To address this question, we substitute the estimates in Tables 3 and the mean values of the variables into equation (11), which decomposes the wage differential into portions due to characteristics, coefficients, and the total mean full-time-part-time wage gap. As mentioned in section 3.4, the first term in equation (11) is weighted by using the coefficients estimates from a pooled sample of the full-time and part-time workers. The pooled full-time and part-time estimates for the three distributions are reported in the last three columns of Table 3. And Table 4 presents the mean full-time/part-time wage differential for different distributions.

Table 4: Decomposition of the Full-time and Part-time Wage Differentials by Distribution

	Characteristics	Coefficients	Total
Normal	0.00130	0.00033	0.00163
Weibull	0.00061	0.00031	0.00092
Exponential	0.00041	0.00029	0.00070

The results indicate that the normal full-time and part-time wage differential is larger than the Weibull and the exponential wage differentials. At first glance, the difference between the normal wage differentials estimates and the non-normal wage differentials estimates appears to be small, but the percentage differential is quite large. For example, the percentage wage differential between the normal, the Weibull and the exponential distributions is 44 percent [(0.00163-0.00092/0.00163) x 100] and 57 percent [(0.00163-0.00070)/0.00163) x 100], respectively. In other words, estimating the wage differential assuming a normal distribution instead of the Weibull and Exponentials distributions increases the full-time and part-time wage differentials by those percentages.

It is observed that in all distributions, differences in the full-time and part-time workers account for a larger portion of the wage differential between them. This seems to suggest that employers pay more attention to differences workers in characteristics in determining the wages for the full-time and part-time workers regardless of the distribution assumed in estimating the wage equation. This finding is consistent with previous studies that have investigated the gender wage differentials assuming a normal distribution (see,Rodgers, (2004), Pissarides et al., (2005); Hirsch, (2005); Ramos et. al., (2015); Manning et. al.,(2008); and Golden, (2020).

6. Summary and Conclusions

This paper investigates the extent to which different distributions of the error term in the wage equation affect the wage differentials between full-time and part-time workers. The results indicate that: (1) different distributions produce different wage estimates. In particular, the Normal distribution wage equation estimates are larger than the Non-Normal distributions wage equation estimates. Such differences in estimates lead to differences in the full-time and part-time wage differentials between the Normal and the Non-Normal distributions. (2) The Normal distribution yielded larger wage differentials than the Weibull and the Exponential distributions. That is, the wage differentials under the Normal assumption may be overestimated. (3) In both the Normal and Non-Normal distributions, the wage differential due to workers' characteristics is larger than the wage differential due to coefficients.

The study also sheds insight into an important wage differential issue among different groups. Since the Non-Normal distributional assumption wage estimates are smaller than the normal assumption, which is mostly assumed in estimating wage equations, it is possible that the estimated wage differentials between groups such as male-female, and black-white in many studies may be overstated. Also, the existence of the size and magnitude of the wage difference may not depend only on characteristics and pay structure, but also the distribution of the wage variable and the method used to estimate the wage equation. The fundamental and practical message is that regardless of the distribution of the error term assumed in the wage equation, policies aimed at improving job characteristics of part-time workers will undoubtedly reduce the part-time wage penalty.

ENDNOTES

1. For a summary of studies that have been done on the full-time and part-time wage differential or the part-time wage penalty for the past decade, see Ramos et. al., 2015, Table 1; and Golden, 2020.
2. This paper is an extension of Baffoe-Bonnie and Gyapong (2018) and some of the discussions and arguments in this section and other sections of this paper rely on the 2018 paper.
3. It must be noted that linear regression models do not require the dependent variable (y) and independent variable (x) to be normally distributed. However, the presence of highly skewed variables can or more likely influence the distribution of the errors making them non-normal. This is precisely why the dependent variable (wage) in

the model has to be checked for normality. See also Vijverberg (1991) for checking normality in the hours of work variable.

4. To save space, the histograms, normal Q-Q plots and box plots were not included in the paper but can be obtained by request.
5. For a detailed discussion of these tests, see Law and Kelton, 1991; ExpertFit software use guide by Law and Associates, 2007.
6. For the derivation of this likelihood function, see Hotchkiss (1989, p. 49). For a complete derivation of this likelihood function, see Hotchkiss, 1989, pp. 75-77.
7. The derivation of the Weibull and exponential likelihood functions equivalent to the Normal distribution can also be found in Baffoe-Bonnie and Gyapong, 2018. Due to the dependence structure of the model (equations 1-3), it is useful to adopt a bivariate Weibull distribution that enables us to assess the correlation between the two variables.
8. Lu and Bhattacharyya (1990) interpret δ as a parameter constraint that provide a stable joint distribution. If $\delta=1$, then the wage (w) and hours of work (h) are independent Weibull distribution, and if $\delta < 1$ implies that w and h are dependent. For the derivation, discussion and application of this bivariate Weibull distribution, see Hougaard (1986), Marshall and Olkin (1988), Lu and Bhattacharyya (1990), and Johnson et al., (1999).
9. Following the Jones, (1983) argument that the wage differential due to differences in coefficients is sensitive to dummy variables, I included the intercept differences, which capture other omitted factors.
10. This paper focuses on the estimation of the total contribution of all the independent variables of the full-time and part-time wage differentials, and no attempt is made to estimate the contribution of each independent variable to the wage differential. See Fairlie, 1999 for the estimation of individual variable to the differential of different

groups. Also, another potential issue of the non-linear decomposition approach is that the decomposition results may be sensitive to the ordering of the variables in the equation. However, Fairlie (2005; 2017) noticed that the ordering has no effect on the total contribution of the variables.

11. The reason may be that the likelihood function of Normal distribution has more maxima than the univariate distribution such as the Weibull, and the Exponential, whose likelihood functions are likely to have only one maximum. The estimates of the location and shape parameters are not reported in Table 3 but can be obtained upon request.
12. Note, the most widely used test of equality of sets of coefficients in two regressions is the Chow (1960) test. However, the Chow test assumes that the variances of the error terms are common between the two regressions. If the variances of the error terms are not the same, the Chow test may be inaccurate. This test statistic has been used by many researchers including Osberg et al. (1987).

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