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The Functional Specification of the Wage-Experience Relationship and Male Wage Inequality in the Philippines: A Decomposition Analysis

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This study analyzed the factors that have contributed to the increase in wage inequality among male workers in the Philippines. Using the Fields (2003) framework as a decomposition platform, the validity of the usual parametric specification of the wage-experience relationship to ascertain the effects of functional misspecification on wage decomposition estimates was investigated. The study found that the quadratic specification of the nonlinear relationship is inadequate, thereby favoring the use of the semiparametric partially linear model, which does not impose any functional assumption on the said relationship.

Keywords: Wages, wage inequality, decomposition analysis

Examining the sources and effects of wage inequality remains one of the most active fields of labor economic inquiry. Gonzales and Miles (2001) noted that the analysis of wage income is important in that it helps in understanding issues related to poverty, migration, and other development-related problems. Aside from this, empirical investigations are needed to understand the intricate interplay among factors in the determination of the levels of and temporal differences in inequality.

Studying male wage inequality in the Philippines is motivated by two important considerations. First, based on the variance of the log of wages, male wage inequality has increased by as much as 20% between 1988 and 1995. Other inequality measures supporting the unambiguous increase in wage inequality are found in Table 1.

Despite this, no empirical evidence has been presented accounting for the said increase. In a related empirical study, Estudillo (1997) found that wage inequality accounts for the largest portion of household income inequality based on household income and expenditures data from 1961 to 1991. However, the data sets used in the study restricted economic investigation to households, and did not include individual workers. Meanwhile, on the econometric front, there is a need to verify whether estimation and inequality decomposition results are robust to the choice of functional specification for the wage-experience relationship. Clearly, data consistent procedures have a critical role to play in this regard.

Despite the value of nonparametric methodologies in providing feasible estimation alternatives to the usual parametric model, these

Table 1
Inequality Measures

Measure	1988	1995	% Change
Relative mean deviation	0.112	0.121	7.63
Coefficient of variation	0.298	0.319	7.02
Standard deviation of logs	0.600	0.657	9.49
Gini coefficient	0.164	0.177	7.59
Theil entropy measure	0.048	0.057	18.65
Theil mean log deviation measure	0.059	0.075	26.25
Variance of the log of wages	0.360	0.431	19.89

methodologies focus only on important determinants, namely education and experience, to avoid the curse of dimensionality. Studies done by Zheng (2000), Ginther (2000), and Gonzalez and Miles (2001) clearly belong to the strand wherein the investigation is limited to the main determinants. As already emphasized in empirical studies, procedures like nonparametric quantile and local constant estimators share the distinction of being robust to specification errors if no omitted variable problems are encountered. However, in practice, there is no certainty that the wage generating mechanism is determined only by the principal determinants of wages, namely, education and experience.

In line with the earnings inequality literature, other factors need to be considered to come up with a more comprehensive treatment. Determinants should not be limited to experience and schooling as other factors representing the impact of preferences, job characteristics, and individual attributes on wage generation are relevant as well. When the set of determinants is expanded, nonparametric methods become computationally costly. Along with the said expansion, issues on dimensionality, interpretability, and predictive flexibility arise. This clearly justifies the consideration of models that can handle the above problems in dealing with linear and nonlinear relationships.

If the object of interest is to quantify the various contributions of plausible sources of inequality, it is warranted to rely on a set of estimable parameters. For instance, Gerfin (1996) noted that while the nonparametric estimator may yield consistent estimates for the labor force participation model, parameters of interest are not identified, thereby acting as a hindrance in providing useful economic interpretations. An important consideration in the estimation of wage function is that estimates for the returns to schooling should be readily available to assess the impact of schooling decisions on wage outcomes, thereby providing indispensable information in the evaluation of educational programs. Obviously, there is a need to balance the demands of specification validity and interpretability. Specification validity calls for the correct application of methods that will handle nonlinear relationships in the model. This, in effect, refers to data-consistent methods. On the other hand, interpretability is an aspect closely related to the ease of understanding economic implications of results.

Of all semiparametric models considered, the partially linear model (Robinson, 1988; Yatchew, 1997) allows the estimation of an unknown function and a set of parameters. The number of applications of this model is still limited, however. Tobias

(2003) used partially linear wage specifications to investigate the relationship among earnings, schooling, and ability. In investigating the determinants of baseball player salaries, Horowitz and Lee (2002) used the partially linear model and found that relative to the parametric specification, it is a better model approximation to the unknown conditional earnings function. Because the role of parameters is important in earnings inequality analysis, the partially linear model is a feasible candidate in that it allows flexibility in dealing with a highly nonlinear component, which is otherwise modeled by polynomial order augmentation and interaction term inclusion. Murphy and Welch (1990) attacked the statistical property of the quadratic Mincerian model by highlighting the higher bias generated by using the quadratic relationship between experience and wages. They claim that the quartic model is less biased relative to the quadratic model. However, augmenting polynomial order is an ad hoc parametric strategy. Zheng (2000) noted the difficulty in arriving at a parsimonious empirical representation of the true conditional mean earnings function of wages.

One of the objectives of this study is to undertake a comparative analysis of estimation and decomposition results from parametric and partially linear models that arise from the empirical treatment of the wage-experience relationship. (In recent literature, however, there is this growing emphasis on the nonlinearity of schooling effects.) The issue of model validity will be investigated using the Yatchew (1997) test that compares the parametric null against the semiparametric alternative. The major goal is to understand the causes of earnings inequality. This study appends a contribution to the literature on inequality decomposition and characterization by investigating the empirical value of the partially linear model in addressing specification issues pertaining to the relationship between wages and experience. It also utilizes the Fields (2003) framework, a useful computational tool that can be readily extended to accommodate counterfactual applications. To the best of my knowledge, no study on Philippine male wage inequality employing both the Fields inequality framework and the partially linear model has been undertaken.

Results from both models indicate that returns to schooling have risen from 1988 to 1995. Based on the factor inequality weights, education accounts for most of inequality among known covariates of inequality. Though this share has declined from 1988 to 1995, education accounts for most of the inequality change. The marriage premium has also declined, irrespective of models considered. However, the residual effect is still considerable as manifested by the contribution of unobservable components to levels of, and changes in inequality.

The study is organized as follows: First, it provides a characterization of the Philippine male labor market. Second, it details the implementation of the decomposition procedure when wage-generating functions follow partially linear specifications. It also discusses the Fields decomposition framework and provides some counterfactual extensions. Third, it explains the various selection rules employed to come up with the final estimation sample as well the list of variables included in the regressions. Fourth, it highlights the results for both the linear and partially linear models as well as the computations for the respective contributions of included variables to inequality. Fifth, it discusses the results within the context of earnings inequality and human capital model. The last section provides conclusions.

THE PHILIPPINE LABOR MARKET: 1988-1995

Interesting accounts on the Philippine labor market covering various topics that associate labor market performance and structure with economic growth in the post-war period had been written by Galenson (1992) and Tidalgo (1988). However, a detailed account focusing on the male labor market has not been previously documented. In this brief review, we analyze changes in the labor market structure of male workers between 1988 and 1995 by focusing on changes in age, occupation, and sectoral composition and educational profiles. Data for tracing labor force changes came from Labor Force Surveys (LFS) conducted in 1988 and 1995.

As shown in Appendix A, the age distribution has undergone changes in that, relative to the 1988 age distribution, the resultant distribution in 1995 appears to be older. In both years, almost 23% of the employed male labor force belongs to the so-called prime-age workers. The labor force, however, is still dominated by agricultural sector, which account for more than 50% of all employed. The size of the agricultural labor force highlights the dependence of the economy on labor-intensive and low value-added sector.

The drop in the agricultural sector's employment share in 1995 can be accounted for by the increase the construction and utility sub-sectors. The growth in the latter may have been influenced by the country's drive to energy sufficiency after suffering an energy crisis in 1992. The precarious situation has paved the way for the increase in energy generation capabilities made possible by legislative initiatives designed to streamline government contracting procedures. As a whole, the service sector's growth in employment share has come from all subsectors, from transportation to recreation services. In some countries, the appreciable shift from industrial to service industries has become the focus of empirical investigations as probable causes of rising wage inequality (Blackburn, 1990). The share of the government sector has also increased.

In terms of occupational structure, managerial and skilled workers' share of total employment has increased with unskilled workers registering a negative growth. The increased share may help account for the increase in inequality as increased variability in terms of wages may occur in groups wherein skill levels are high. The educational profile of male workers has also improved over time. The share of workers who have not attended high school has declined. There have been remarkable increases in high school graduates as well as workers who have at least attended college. However, the share of workers with college degrees has declined over time.

Between 1988 and 1995, several institutional changes that may have material effects on the male labor market have occurred. In 1989, the Philippine Congress enacted the salary standardization law that has sought to adjust wages in the public sector. This law created a tangible framework that would facilitate future reviews of the salary schedule of the government. This is due to the recognition that the wage schedule may be rendered relatively inferior as factors, like inflation and private sector competition, may take their toll on government hiring positions. Legislative interest in the welfare of public sector workers has been further manifested in a joint resolution in 1993, calling for an update of the wage schedule done in 1989 for civilian and uniformed members of the public sector. The resolution cited the availability of funds in the General Appropriations Act to carry out the comprehensive wage increase via updating. Recently, Congress has enacted a law supporting the increase in salaries of members of the judiciary.

In cognizance of the needs of workers in the private sector, the government has also affected an increase in the minimum wage in 1989. This legislative act, known as the Wage Rationalization Act of 1989 (Republic Act No. 6727) instituted the increase in minimum wages regardless of gender. A penalty structure for non-compliance was also formulated. The increase in minimum wage was PHP25 regardless of sectoral affiliation in the private sector. Galenson (1992) noted that the increase, 39% relative to the 1986 level, was partly due to union pressure. But because of inflationary pressures, real wages have declined. By virtue of the legislative enactment, the government has established regional wage boards, which became mechanisms for wage increases and effectively decentralized approval for wage increases. The act also abolished the National Productivity Commission and National Wage Council, paving the way for the creation of the National Wages and Productivity Commission.

WAGE INEQUALITY DECOMPOSITION

A Semiparametric Model Based Approach

The usual parametric modeling strategy calls for the ad hoc inclusion of higher ordered polynomials to approximate nonlinear relationships in the conditional mean function. This strategy starts with a choice of variable, which is then subjected to transformations. An alternative to this is to assume a nonparametric component that duly accounts for the nonlinear behavior of the conditional mean function relative to the variable under question while maintaining parameterization of the linear component. Empirical labor research usually concludes that the wage function is concave in experience and linear in schooling (Lemieux, 2002; Willis, 1987). But the concavity of the wage function is the by-product of a quadratic specification. The partially linear model does not assume that the highest polynomial order is two, that is, the empirical relationship is determined by the data.

Consider two models, which are assumed to be the proper representations of the conditional mean functions of wages at time *t* and *s*.

$$\log W_i^t = x_i^{t\prime}\beta_t + h^t\left(z_i^t\right) + \varepsilon_i^t \qquad (1)$$

$$\log W_i^s = x_i^{s\prime}\beta_s + h^s\left(z_i^s\right) + \varepsilon_i^s \qquad (2)$$

where log W_i refers to the natural logarithm of the wage rate; $\boldsymbol{x}_i$ represents the vector of worker *i*'s attributes; h^t (z_i) refers to the nonparametric function; and $\mathring{a}_i$ is the error term. (Note that the superscripts *t* and *s* refer to different years.) The above equations are the semiparametric counterparts of the usual linear regression models employed for both periods. For the coefficient vector $\hat{a}_t$ to be identified, exclusion restrictions need to be imposed on the vectors $\boldsymbol{x}$ and z, that is, components of $\boldsymbol{x}$ should not be perfectly predictable by z (Robinson, 1988).

Based on the Robinson (1988) estimation procedure for the partially linear model, the estimating equations are derived by deducting their respective expectations conditional on variable z_i on which support for the nonparametric function is defined. With the assumption that the error vector has zero mean, the nonparametric component cancels out, thereby leaving only the parameters of interest to be estimated. The nonparametric component for this study is assumed to be experience. This avoids the ad hoc functional specification for the said covariate.

An alternative to the Robinson (1988) estimator has been provided by Yatchew (1997), which relies on differencing techniques. Given the partially linear model, estimation of the parameters is arrived at by eliminating the nonparametric component by way of differencing, which does not involve nonparametric regression estimation of various conditional moments. Critical in this estimation method is the assumption that as sample size increases, the difference between $h(z_t)$ and $h(z_{t-1})$ would be negligible. (A clarification is in order. While the concept of differencing is more understandable within the time series context, its implementation using cross sectional observations relies on the fact that the value of the nonparametric function for two adjacent and independent observations should be close to zero. Due to the independence and smoothness assumptions, the nonparametric component will be eliminated.)

Using data for year *s*, this implies that the model to be estimated is given by

$$\log w_i^s - \log w_{i-1}^s = (x_i^s - x_{i-1}^s)'\beta_s + \left(\varepsilon_i^s - \varepsilon_{i-1}^s\right) \quad (3)$$

The parameter vector would now be estimated by way of least squares without the constant term. The estimator for the coefficient vector is given as

$$\hat{\beta} = \frac{\sum\left(\log w_i^s - \log w_{i-1}^s\right)\left(x_i^s - x_{i-1}^s\right)}{\sum\left(x_i^s - x_{i-1}^s\right)^2} \qquad (4)$$

In line with the estimation, the model uses *n*-1 observations and efficiency of the parameter estimates would be improved relative to

Robinson's (1988) kernel-based method by increasing the differencing order. It also provides a framework for testing the specification of the linear model against the partially linear model with respect to the specification of the nonlinear component. The method however, though less tedious, suffers from limitations. According to Yatchew (1997), this is because it is applicable only if the number of nonlinear components does not exceed three. Yatchew explained that a lot of studies could still benefit from the simple estimation procedures due to limited number of potentially nonlinear relationships. Another criticism has been provided by Greene (2003), who noted that the convergence assumptions that lead one to disregard the nonparametric function might not be realized using actual data.

The testing method compares the sum of squared residuals of the restricted and unrestricted models with the linear model representing the restricted model. This is understandable since the nonparametric function does not impose a parametric structure on the relationship between earnings and experience.

Consider two models, one restricted (M_r) and one unrestricted (M_{ur}). The test statistic that compares the parametric null against the semiparametric alternative is given by

$$T_n = \frac{n^{1/2}\left(SSR(M_r) - SSR(M_{ur})\right)}{SSR(M_{ur})} \sim N(0,1) \quad (5)$$

Based on the preceding equation, the test statistic has a standard normal distribution (for derivations see Yatchew, 2003). The parametric model represents the restricted model while the semiparametric partially linear model represents the unrestricted model due to the nonparameterization of the nonlinear relationship. As noted by Yatchew (2003), since the test procedure is a one-sided test, large values of the test statistic would signal rejection of the null hypothesis, which would be indicative of the modeling shortcomings of the nonlinear relationships assumed in the parametric model.

In the literature, the estimator for the respective nonparametric components would be computed by assuming that the parametric component is known. Specifically, the said estimator is given as

$$h^s\left(z_i^s\right) = \sum \omega_i^s \left(\log W_i^s - x_i^s{}'\hat{\beta}\right) \quad (6)$$

where $\grave{u}_{it}$ corresponds to the kernel weights.

Specifically,

$$\omega_i^t = \frac{K\left(z^t - Z_i^t\right)/h}{\sum_j K\left(z^t - Z_j^t\right)/h} \quad (7)$$

where h is the parameter governing the smoothness of the nonparametric regression function.

Although nonparametric procedures can implement the decomposition procedure while attaining minimal errors, such procedures render interpretation difficult especially in quantifying covariate specific effects. Nonparametric regression estimates would be in the form of multi-dimensional regression surfaces that would render interpretability of results difficult.

There are various procedures through which the nonparametric component can be estimated. These methods include the use of local linear regression, kernel regression, and spline methods. However, this study will simply implement a one-dimensional nonparametric regression estimator with a quartic kernel serving as the kernel function. As known in the nonparametric literature, nonparametric regression can simply be translated as local constant weights for the admissible regressors. The regression estimates are determined largely by the magnitude of the bandwidth smoothing parameter. For bandwidth choices, automatic selectors like the generalized cross validation criterion are available.

Because the procedure allows the transformation of a semiparametric estimation problem into a parametric one, Fields' (2003) decomposition strategy to settle the "levels" and "differences" questions on inequality can be applied. This is an improvement over the simple variance accounting framework in that it is applicable to any inequality measure other than the variance.

Sources of Inequality and the Fields Decomposition Framework

Covariates of wages and probable causes of inequality. Levy and Murnane (1992) outlined the requisites of wage inequality analysis stressing the need to identify the various factors that have a plausible impact on the distribution of wages. Earnings inequality analysis hinges on the validity of the income generating mechanism. As explained by Blackburn (1990), Bell, Rimmer, and Rimmer (1994), and Cardoso (1998), determinants of within group inequality usually include, but are not limited to, experience, schooling investments, sectoral affiliation, industry affiliation, residential location, and marital status.

As Blackburn (1990) argued, relatively young workers have inferior experience profiles compared to more experienced workers. So, the differential composition of the labor force in terms of experience profiles may actually contribute to rising inequality as new entrants receive relatively low wages compared with those who have accumulated considerable experience, especially during times of rapid increases in returns to experience. Since age is instrumental in the computation of potential experience, the latter may also be reflective of demographic shifts over time. Wage inequality may rise during periods wherein demographic transitions are more pronounced, as the skill differentials between young and old workers may appear to widen.

Inequality increases may also be triggered by the differential composition of the labor force based on educational attainment. Education differentials as manifested in high school-college wage differentials are a case in point. Demand and supply conditions affect the market for skills that high school and college graduates may offer. If the relative demand for skills favors college graduates, then this may affect the distribution of wages and hence raise inequality. However, in the analysis of within group inequality, certain aspects associated with schooling quality need to be considered in understanding how schooling decisions would affect inequality. As investigated by Martins and Pereira (2004), over-education for instance may contribute to increased wage inequality.

Institutional features that contribute to the non-equality of a worker's marginal productivity to his wage also generate earnings inequality. Studies by DiNardo, Fortin and Lemieux (1996), Cardoso (1998), and Lemieux (2002) clearly indicate that minimum wage setting is an important determinant of wage inequality. Minimum wages are known to compress the wage distribution. Wage settings in private and government sectors also contribute to earnings inequality since in the latter, wages are determined by conditions other than those shaped by market forces. On the other hand, the private sector maximizes profits. Psacharopoulos (1994) notes that returns to schooling in institutions wherein the setting is undoubtedly non-competitive are inferior relative to institutions wherein market forces determine wages.

The marriage premium is also an important source of inequality. A study made by Blackburn (1990), for instance, concludes that marriage accounts for a substantial portion in explaining within group inequality. The link may be in the form of more favorable productivity effects on married workers as opposed to single workers.

Finally, as noted by Bell, Rimmer, and Rimmer (1994), the practice of including dummy variables pertaining to regional residence, industry affiliation, and occupation is useful in controlling the effects of human capital with or without the presence of schooling and experience. In the analysis of within group wage inequality, changes in the industrial and occupational mix of skills may have a profound effect on the distribution of wages. One important manifestation is the drive towards the increasing use of highly skilled workers or the adoption of skill-biased technologies that result in reduced relative demand for lower skilled workers.

The Fields decomposition framework. As mentioned, Fields' framework is used to analyze the individual contributions of factors to inequality. The Fields framework encompasses familiar decomposition frameworks like the Juhn, Murphy, and Pierce (1993) approach wherein it provides necessary computations for the price and quantity effects. One notable application of the Fields framework has been undertaken by Kang and Yun (2002) who analyzed changes in Korean wage inequality and decompose changes into price, quantity, and residual effects by unifying the Juhn, Murphy, and Pierce and the Fields factor inequality approaches.

Given the determinants presented in the preceding section, these are the details of the Fields inequality decomposition framework. Consider the equation $\log W_i^t = x_i^t{}'\beta + \upsilon_i^t$. Following Fields, $Cov\left(\log W_i^t, x_i^t{}'\beta\right)$ is simply the sum of covariances between $x_i^t{}'\beta$ and $\log W_i^t$, implying that the covariance of $\log W_i^t$ with itself is just the variance. So, in effect, the variance of the log of wages is equal to the sum of covariances.

As discussed in Fields, the contribution of the j^{th} factor to overall inequality, θ_j^t, is conveniently given by the following expression:

$$\theta_j^t = \frac{\hat{\beta}_j^t \hat{\sigma}\left(x_j^t\right)\hat{\rho}^t}{\hat{\sigma}\left(\log W^t\right)} \tag{8}$$

where $\hat{\rho}^t$ pertains to the correlation coefficient of the log of wages and the factor considered at time t, $\hat{\beta}_j^t$ refers to the coefficient of the factor j, and $\hat{\sigma}\left(x_j^t\right)$ is just the variance estimator.

The above formula is implementable within the parametric framework and can simplify tedious computations for ascertaining the inequality contribution of various factors. As shown, the contribution to inequality of factor j may be either positive or negative, depending on the estimated coefficient as well as the correlation structure of included covariates. The validity of the correlation structure depends greatly on whether there are measurement errors or omitted variables. The consistency of coefficient estimates depends on the validity of the parametric specification of the model. Thus, the contributions to inequality are subject to the validity of the specification used.

As also shown by Fields (2003), it is possible to extend the framework to the decomposition of changes in inequality between two time periods. The general formula to compute for the changes in inequality is given as

$$I_t - I_s = \sum_j \left(\theta_j^t I_t - \theta_j^s I_s\right) \tag{9}$$

where θ_j^t is the contribution of factor j at time t to overall inequality during that period and I_t refers to the scalar value of an inequality measure at time t. Basically, factor j's contribution to changes in inequality is just the difference of inequality weighted by the share of the factor in question. From the formula, it is clear that the contribution of a factor to changes in inequality depends on the estimated coefficients and the variability of the logarithm of wages. The advantage of the above framework is that it allows the computation of changes in inequality using various inequality estimates.

Counterfactual Exercises

In this section, extensions to the Fields decomposition framework by way of counterfactual analyses will be discussed. These extensions would be of utmost benefit especially when dealing with parametric functional forms but they can also be of use in semiparametric regression settings except that the nonparametric components may be difficult to be subjected to counterfactual designs. As emphasized by Lemieux (2002), counterfactual exercises that involve the distribution of a variable or a residual may be easier when done using samples with the same number of observations. However, it is possible to employ such methods to nonparametric functional estimates, which represent marginal effects of the variable under scrutiny. For instance, one may create a counterfactual functional estimate by using the nonparametric function estimated in 1988 instead of 1995 to determine the effect on wages when the marginal effects emanate from 1988.

The use of counterfactual exercises allows a researcher to determine the impact of an individual or collective set of variable parameters on the dependent variable. Following Lemieux (2002), an important, yet minor, extension to the above decomposition procedure is to introduce counterfactual measures that answer the following questions: (1) What would the inequality weights have been in 1995 if worker attributes had remained at their 1988 level and returns have changed? and (2) What would the inequality weights have been in 1995 if returns remained invariant at their 1988 level and worker attributes have changed?

To elucidate further, consider the following decomposition formula for the j^{th} explanatory variable:

$$\theta_j^t = \frac{\hat{\beta}_j^t \hat{\sigma}\left(x_j^t\right)\hat{\rho}^t}{\hat{\sigma}\left(\log W^t\right)} \tag{10}$$

Instead of using the above coefficients and covariates, two counterfactual estimates can be made, namely

$$\theta_{jc}^{t1} = \frac{\hat{\beta}_j^s \hat{\sigma}\left(x_j^t\right)\hat{\rho}^t}{\hat{\sigma}\left(\log W^t\right)} \tag{11}$$

$$\theta_{jc}^{t2} = \frac{\hat{\beta}_j^t \hat{\sigma}\left(x_j^s\right)\hat{\rho}^s}{\hat{\sigma}\left(\log W^s\right)} \tag{12}$$

Equation (11) simply computes for the resultant factor inequality share for covariate j at time t if the coefficients used belong to that of period s. When subtracted from equation (10), we would have the effect of coefficients on the factor inequality weight.

Algebraically, the difference would be expressed more simply as

$$\Delta\theta_j^{t,coef} = \frac{\left(\hat{\beta}_j^t - \hat{\beta}_j^s\right)\hat{\sigma}\left(x_j^t\right)\hat{\rho}^t}{\hat{\sigma}\left(\log W_i^t\right)} \tag{13}$$

The magnitude would simply reflect the differences in coefficients as the correlation structure is preserved.

On the other hand, to determine what the impact would be of the distribution of covariates on the factor inequality share, equation (12) can be implemented. When subtracted from equation (10), the resultant magnitude would simply represent the effect of covariates on the factor inequality share. The effects of the covariates would be manifested in the differences in correlation structure which includes the variation of wages at their respective time periods.

$$\Delta\theta_j^{t,x} = \hat{\beta}_j^t \left[\frac{\hat{\sigma}\left(x_j^t\right)\hat{\rho}^t}{\hat{\sigma}\left(\log W_i^t\right)} - \frac{\hat{\sigma}\left(x_j^s\right)\hat{\rho}^s}{\hat{\sigma}\left(\log W_i^s\right)}\right] \tag{14}$$

Note that when

$$\frac{\beta_j^t \hat{\sigma}\left(x_j^t\right)\hat{\rho}^t}{\hat{\sigma}\left(\log W_i^t\right)} > \frac{\beta_j^s \hat{\sigma}\left(x_j^t\right)\hat{\rho}^t}{\hat{\sigma}\left(\log W_i^t\right)}$$

the counterfactual exercise of using returns or coefficients at time s instead of t when the period of concern is time t would result in a lower inequality contribution. Likewise, when

$$\frac{\beta_j^t \hat{\sigma}\left(x_j^t\right)\hat{\rho}^t}{\hat{\sigma}\left(\log W_i^t\right)} > \frac{\beta_j^t \hat{\sigma}\left(x_j^s\right)\hat{\rho}^s}{\hat{\sigma}\left(\log W_i^s\right)}$$

the counterfactual exercise of using characteristics or attributes at time *s* instead of time *t* when the period under scrutiny is time *t* would result in a lower inequality contribution.

DATA AND VARIABLES

The October rounds of Philippine Labor Force Surveys (LFS) conducted in 1988 and 1995 were used for this study. The LFS is undertaken by the National Statistics Office (NSO) to gather relevant information on labor market activities of individuals during the previous quarter (July-September). It is a representative multi-stage survey that uses the sampling frame of the Integrated Survey of Households (ISH).

This study focuses on non-agricultural workers in the government and private sectors, thereby eliminating from the estimation sample individuals who work for informal or household businesses. Workers with negative potential experience are not included. The working population is restricted to the 15-64 years old age group. Individuals below the age of 15 are not included because, officially, they are not part of the labor force. Military personnel and domestic helpers are also left out. With these exemptions, the sample sizes are 5,978 in 1988, and 8,287 in 1995.

The important variables needed for the empirical investigations are briefly described here. Total earnings refer to accumulated wage earnings and allowances for three months only. To get the hourly wage rate, one simply divides total earnings by total hours worked. Education is measured by years of schooling and calculated based on education recodes. Potential experience is computed following the Mincerian way, that is, age minus years of schooling minus six. To ensure comparability, the consumer price index for the computation of real hourly wages with the base categories pertaining to 1988 for the year and National Capital Region for the location was used.

Variables like regional residence and urbanity to control for geographic effects on wage variation were also included. Worker characteristics pertaining to sectoral affiliation (private or government sector worker), marital status, industry affiliation, and occupational categories are also included. Descriptive statistics for the variables included in the regression models are shown in Appendix B.

COMPARATIVE RESULTS

Models

The empirical strategy starts with the comparison of models that differ with respect to the treatment of the expression pertaining to the assumed functional specification for the earnings-experience relationship.

For the purpose of conducting a preliminary comparative analysis, the following specifications are adopted:

$$\log W_i^t = g(EXP_i^t) + \beta_1 SCH_i^t + \beta_2 MS_i^t + \beta_3 URB_i^t + \beta_4 PRIV_i^t + \sum_j^J \beta_j IND_i^t + \sum_k^K \beta_k OCC_i^t + \sum_l^L \beta_l REGN_i^t + \varepsilon_i^t \quad (15)$$

$$\log W_i^t = \beta_0 + \beta_1 SCH_i^t + \beta_2 MS_i^t + \beta_3 URB_i^t + \beta_4 PRIV_i^t + \beta_5 EXP_i^t + \beta_6 EXP_i^{t2} \sum_j^J \beta_j IND_i^t + \sum_k^K \beta_k OCC_i^t + \sum_l^L \beta_l REGN_i^t + \varepsilon_i^t \quad (16)$$

Equation 15 is the partially linear representation of the general wage function. Equation 16 is the usual parametric wage regression function. The main difference between the two specifications is that the former does not impose a functional assumption on the variable experience while the latter subscribes to the quadratic specification of the earnings-experience relationship. Both specifications assume, however, that the earnings-schooling relationship is linear. This may also be subjected to another empirical investigation as there is increasing evidence pointing to the nonlinearity of the said relationship. The other covariates like marital status (MS), urbanity (URB), private worker (PRIV), regional residence (REGN), industry (IND) and occupational categories (OCC) have been assumed to exert a linear effect on earnings.

Estimates

Parametric and semiparametric estimation results based on assumed earnings generating mechanisms are reported in Appendix C. Estimation methods have been carried out using Xplore and Gauss programs, which are available upon request. The earnings-experience profiles for the parametric model are concave, consistent with the predictions of the human capital model. This means that the log of wages increases at a diminishing rate relative to experience. So, the longer a worker stays employed, the more experience he accumulates, but the contribution of an additional year of experience to a wage increase would be lower relative to the prior contribution.

However, as shown in Figure 1, the relationship between earnings and experience seems to be non-concave over the entire support of experience. Based on the estimated nonparametric effects, there are intervals within the support of experience wherein the relationship is convex, thereby indicating that the marginal contribution of experience within the said range is actually increasing. This means that the assumed parametric structure of such a relationship may be inadequate when compared with a data consistent estimator. It also shows that the returns to experience are considerable for workers belonging to the high experience range.

The functional assumption on the earnings-experience relationship also affects the estimates of the returns to schooling as represented by the coefficient estimate of schooling. It is clear that the returns to schooling have increased from 1988 to 1995, regardless of model considered. However, in terms of nominal returns, the linear model registered much higher returns relative to that of the partially linear model.

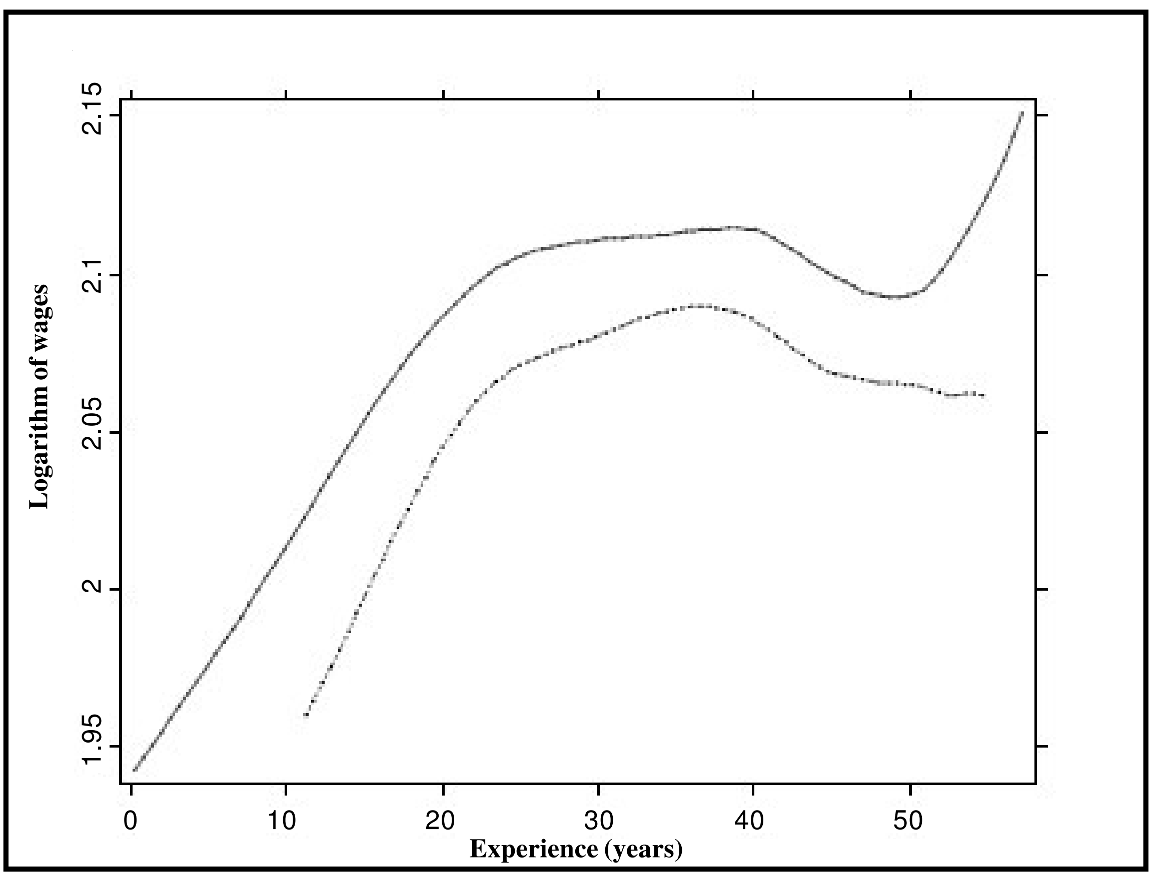

Figure 1. *Nonparametric effect of experience, 1988 (solid) and 1995 (broken)*

Another point of contrast concerns the private-public wage premium. The coefficient estimate represents the difference between the conditional mean of wages between public and private workers, holding other factors constant. When positive, workers in the private sector are better off. Both models confirm the non-existence of the private-public wage premium. This implies that regardless of model, workers in the private sector are worse-off relative to their public sector counterparts.

It is also of interest to note that the marriage premium has fallen from 1988 to 1995, regardless of model considered. However, the fall is greater for the linear model than in the partially linear model. Despite this, the evidence show that both model support the existence of the marriage wage premium for male workers, which is consistent with the literature investigating returns to marriage (see Gray, 1997; Hersch & Stratton, 2000).

From 1988 to 1995, workers in urban areas are also worse-off based on partially linear model estimate. This implies that relative to workers in rural areas, urban workers are better off in 1988 than they were in 1995. On the other hand, based on the linear model, urban-based workers in both years are better off.

It is also important to note the similarities across models. Relative to workers in the National Capital Region (the left out regional dummy), both models show that workers elsewhere are worst off as shown by the significantly negative coefficients. Relative to the left out category for occupation, all occupation dummies in both models have similar coefficient signs. With the exception of the construction dummy, industrial affiliation dummies in both models appear to have similar signs.

Test Results

While this study focuses on the validity of the quadratic specification relative to the partially linear model, the Yatchew test was used to test different parametric models that emanate from various treatments pertaining to the functional relationship between earnings and experience. To do this, other variants namely, linear, quartic, and cubic in experience, were estimated. The test procedure has been carried out in Splus by modifying Yatchew's scripts. Table 2 shows the results.

As can be seen, all parametric specifications are rejected in favor of the partially linear model. This supports Zheng's (2000) contention that searching for a parsimonious model that adequately handles nonlinear relationships is difficult. In view of this development, we continue to employ the parametric model in the subsequent decomposition exercises to ascertain the impact of the misspecified

Table 2
Goodness of Fit Tests

Model	1988	1995
Linear in experience	12.103 (0.000)	18.246 (0.000)
Quadratic in experience	11.246 (0.000)	17.572 (0.000)
Cubic in experience	11.203 (0.000)	17.469 (0.000)
Quartic in experience	11.203 (0.000)	17.433 (0.000)

Note: p-values are enclosed in parentheses.

functional relationship between experience and wages.

Inequality Contributions

Appendix D details the inequality contributions from individual covariates. As mentioned earlier, the contributions largely depend on the respective coefficient estimates and correlation structures. It is important to note that even when the factor inequality weights have increased from period one to period two, it does not follow automatically that the resultant contribution to changes in inequality between the two periods reflect the said increase in factor inequality weights.

The calculations indicate that it is important to rely on factor inequality weights to properly discern the relative importance of considered factors that are important in inequality analysis. It is clear from both methodologies that the main contributor to intra-period inequality is the residual or the set of unobservable components in the model. This is not surprising as studies analyzing the impact of residual inequality have documented its substantial role in the determination of wage inequality (see Blackburn, 1990; Juhn, Murphy, & Pierce, 1993; Lemieux, 2002). For instance, the contribution to inequality using the linear model for each period is about two-thirds, indicating the substantial contribution of within group inequality. In the case of the partially linear model, the contribution to inequality of the residual rose to a high of 74%, indicating that included regressors have a joint contribution amounting to a measly 20%.

Schooling remains the most important factor among the identified covariates in terms of inequality contribution. Close to one-third of the inequality determined by the observable characteristics has been represented by schooling. However, the contribution from 1988 to 1995 fell. For the partially linear model, the contribution is much less relative to the linear model counterpart.

Occupation accounts for a significant portion of inequality for both models in both years, followed by location preferences and industry affiliation. However, the portion of inequality accounted for by occupation has declined. Location's inequality contribution has also declined from 1988 to 1995 for both models. Industry affiliation's contribution to the inequality gap is positive in both models, contrary to the ambiguous results for occupation and regional location.

In terms of explaining inequality changes, schooling appears to have a positive influence on the increase in inequality from 1988 to 1995 in both models. Sectoral affiliation has a negative impact on the change according to the partially linear model and positive effect based on the linear model. Marital status appears to negatively affect the inequality change. Based on the partially linear model, occupation has a positive effect while the linear model shows that its effect is negative. Industry affiliation is partly responsible for the widening inequality gap. Divergence in impact is also seen for regional residence as the partially linear model registers a negative impact, while the linear model registered a positive impact. Finally, both models show that the residual effect works to widen the inequality gap.

Counterfactual Estimates

Appendix E shows the counterfactual exercises done using both models. Considering the coefficient effects of schooling, the counterfactual exercise involved seeks to quantify the effects of changing coefficient structures on inequality factor weights. In the case of the partially linear model, when the coefficient estimate on schooling in 1988 is used to simulate the resultant inequality shares for 1995, the factor inequality share of schooling declines while it increases when the educational profile in 1988 is used. So, if the educational profile remained the same in both years, the contribution of schooling would be greater, suggesting that changes in schooling returns may worsen the inequality picture. The same patters are also observed for the linear model.

It is also interesting to note that for the parametric model, the coefficient effects work towards the increase of within group inequality represented by the residual. However, the characteristic effects would lead to the decrease of the residual effect. In contrast, based on the partially linear model, the effect of using returns to attributes in 1988 instead of returns in 1995 is to reduce the effect of the residual on inequality. Likewise, the same effect can be inferred when characteristics in 1988 instead of 1995 are used.

In the linear model, the collective coefficient effect of occupation is to increase the overall inequality share of occupation while the opposite is true for the partially linear model. When characteristics in 1988 instead of 1995 attributes are used, the share of occupation to inequality is increased. The effects of industry would depend on the model choice. Under the partially linear model, when the returns and characteristics in 1988 are used instead of those in 1995, the inequality contribution of industry would be increased. This is totally in contradiction to the inferences derived from the linear model. Estimates from the partially linear model show that, in terms of location effects, the over-all coefficient effect of regional residence is increased. In terms of characteristics, the contribution would be lower. For the linear model, the same effects can be inferred from the results.

DISCUSSION

The econometric exercises have pointed out several interesting results pertaining to the proper treatment of the nonlinear component of the wage equation. The use of the partially linear model has revealed that the wage-experience profile is not entirely concave, contrary to the resultant profile arrived at by employing the quadratic model. Thus the use of the semiparametric model may be beneficial in that there is no need to use higher order polynomials to model the wage-experience relationship as practically done by using the quartic wage function (Murphy & Welch, 1990). The results confirm that the usual parametric treatment is not adequate, thereby reinforcing findings made in studies that have subjected the parametric specification to consistent tests. An apparent question that may be raised, which is totally consistent with the results, concerns the relevance of the human capital theory on which the estimation methods should be based. While this study advocates the use of partially linear model to address specification issues, the advocacy concerns the statistical treatment of the specification problem, not the economic underpinnings of the econometric investigation. This is closely in line with studies that only subject the specification to model validation but leave intact the composition of variables that constitute the economic approach.

The sheer magnitude of the residual effect on inequality is remindful of the fact that unobserved variables pertaining to the skills and abilities of workers, their working environment and their interactions within a policy environment remain important in modeling the wage function. As already discussed, schooling quality may affect the underlying distribution of abilities which may worsen within group inequality. The results present a consensus that the within group inequality component of overall inequality accounts for the substantial part of earnings inequality. This implies that workers belonging to the same group are still heterogeneous, indicating that distinctive bundles of skills and other latent abilities allow for the possibility of a differentiated wage structure.

The results easily establish education as a vital component of policy interventions, the objectives of which are closely intertwined with the reduction of wage inequality. For instance, growing inequality in educational attainment results in rising inequality. Aside from the educational profiles of workers, inequality may also be influenced by the rate of increase in the returns to education. Thus, inequality may still increase even when the educational profile remains constant over time as long as the labor market permits returns to schooling to rise.

Aside from education, which is determined by workers themselves, other factors that consider the interplay among workers' decisions, like institutional and market structures, may play a major role in inequality generation. As already known, sectoral decisions of workers regarding their employment preferences are important. The different incentive structures in private and government sectors affect the way the two said sectors behave in wage setting. Minimum wage legislation and firm compliance, legislative wage setting for government workers, and their position in the wage determination processes are just some of the institutional factors that determine the extent of inequality.

Wage inequality may also be understood via the marriage premium especially when it is interpreted as connected to the productivity of married male workers relative to single ones. An interesting question that may attract interest concerns the comparative inequality analysis of married and unmarried male workers.

The results also indicate that industry and occupation differentials, as indicated by the differing estimates, have roles to play in the generation of inequality. Inequality arises partly due to the relative concentration of skilled and unskilled workers in various industries.

Location tastes also have an impact on inequality especially in cases wherein the resultant increase in the concentration of workers in a given place is caused by the influx of unskilled workers. Thus, migration of workers has a very strong role to play in the determination of the relative demand and supply of skilled and unskilled workers. The dynamics of this interaction would either lead to an increase in inequality.

CONCLUDING REMARKS

This study applies both parametric and semiparametric approaches to determine the effects of adopting different modeling strategies when it comes to the relationship between wages and experience. Semiparametric estimates indicate that the said relationship is not entirely concave, supporting the contention that dependence on an assumed functional structure for the said relationship may generate erroneous estimates for the linear part of the model. Test results show that searching for a parsimonious specification of the nonlinear relationship is difficult. Adopting the partially linear model alternative, which is proven to be adequate by formal testing, mitigates this difficulty. Based on the results, this study forwards a skeptical stance to the usual parametric treatment of the nonlinear relationship. The results are in line with studies that have scrutinized the usual parametric treatment. Though the econometric exercises provide important preliminary results to understand the usefulness of semiparametric procedures, the main interest of this paper is to simply account for the temporal behavior of earnings inequality.

This study applies the Fields (2003) inequality decomposition framework, which proved useful in quantifying the relevant inequality factor weights that serve as indicators of relative factor importance. The platform on which this framework is based on is the semiparametric estimation framework, which is one of the main contributions of this study.

Based on the results, within group inequality remains the principal contributor to the increase in inequality observed from 1988 to 1995, indicating that other unobservable worker and firm characteristics central to the explanation of wage differentials remain unaccounted for due to the limitation of the data set employed. The results also confirm that education remains the most important determinant of inequality aside from the residual. This implies that one way that inequality may be reduced is to focus on the delivery of educational services to reduce the inequality of education. It has also been found that experience may not have the concave effect on earnings, implying that at a certain point, post schooling investments of workers may not fall but rather increase. Interesting results have been found regarding the role of industry wage differentials, wage premium, private-public wage differentials and location differential on inequality generation.

The counterfactual exercises provided insights as to how the inequality factor weights may behave when various scenarios concerning the utilization of coefficients or returns and characteristics are investigated. There are marked differences between the partially linear and linear models when it comes to the evaluation of over-all effects. The models differ when it comes to residual, industry affiliation, and regional residence. Similar effects have been noted, however. These are schooling, occupation, marital status, and urbanity.

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Appendix A
Characterization of the Labor Force

Age Group	1988	1995	% change
15 to 19	0.116	0.106	-9.200
20 to 24	0.134	0.121	-10.700
25 to 34	0.260	0.237	-9.500
35 to 44	0.211	0.228	7.600
45 to 54	0.151	0.163	7.000
55 to 64	0.086	0.097	11.500
65 over	0.043	0.048	10.600
All employed males	**1.000**	**1.000**	

Industry affiliation	1988	1995	% change
Agriculture, Fishery and Forestry	**0.551**	**0.514**	**-7.200**
Industry	**0.163**	**0.174**	**5.800**
Mining and quarrying	0.010	0.006	-7.400
Manufacturing	0.087	0.085	-2.300
Food beverage and tobacco	0.026	0.026	0.600
Importable manufacturing	0.011	0.014	18.400
Traditional exportable/importable	0.035	0.026	-32.900
Non-traditional exportable/importable	0.015	0.019	20.900
Construction	0.060	0.077	21.200
Electricity, gas and water	0.005	0.006	4.700
Service Sector	**0.286**	**0.312**	**8.600**
Transport, storage and communications	0.071	0.087	17.600
Trade	0.074	0.079	5.300
Finance, Insurance and Real Estate	0.018	0.020	9.000
Private and government services	0.105	0.108	2.300
Recreational services, hotels	0.016	0.019	15.600
All employed males	**1.000**	**1.000**	

Occupation	1988	1995	% change
Professionals and managers	0.035	0.040	13.000
Skilled and middle level workers	0.108	0.117	7.800
Low wage workers	0.857	0.842	-1.700
All employed males	**1.000**	**1.000**	

Educational Attainment	1988	1995	% change
No grade completed	0.040	0.033	-17.900
Grades I to V	0.246	0.216	-12.300
Elementary graduate	0.236	0.225	-4.600
1st to 3rd year high school	0.136	0.141	3.300
High school graduate	0.179	0.207	15.600
College undergraduate	0.090	0.105	16.900
College graduate or higher	0.072	0.072	-0.300
Not reported	0.000	0.001	2.500
All employed males	**1.000**	**1.000**	

Appendix B
Descriptive Statistics

Variable	1988		1995	
	Mean	Std Dev	Mean	Std Dev
Log Wage	2.012	-0.600	2.059	-0.657
Experience (EXP)	19.652	-11.313	19.950	-11.726
Schooling (SCH)	9.784	-3.095	9.813	-3.039
Private (PRIV)	0.776	-0.417	0.689	-0.463
Marital Status	0.740	-0.439	0.778	-0.416
Occupational Categories (OCC)				
Professional, technical and related workers (PROF)	0.114	-0.318	0.101	-0.301
Administrative, executive and managerial workers (ADMIN)	0.021	-0.144	0.035	-0.185
Clerical workers (CLERICAL)	0.108	-0.311	0.098	-0.298
Sales workers (SALES)	0.053	-0.224	0.061	-0.239
Service workers (SERVICE)	0.134	-0.340	0.163	-0.369
Industry Affiliation (IND)				
Mining and quarrying (MINING)	0.019	-0.138	0.011	-0.104
Utilities (UTILS)	0.023	-0.149	0.017	-0.128
Construction (CONST)	0.111	-0.314	0.135	-0.342
Wholesale and retail trade (TRADE)	0.069	-0.253	0.080	-0.272
Transportation, storage and communications (TRANSPO)	0.173	-0.378	0.171	-0.377
Financing, insurance, real estate and business services (FIREBS)	0.063	-0.243	0.072	-0.258
Community, social, and personal services (COMM)	0.318	-0.466	0.304	-0.460

Regional residence (REGN)				
Urbanity (URB)	0.724	-0.447	0.803	-0.398
Region 1	0.059	-0.235	0.063	-0.243
Region 2	0.029	-0.168	0.030	-0.170
Region 3	0.128	-0.334	0.098	-0.298
Region 4	0.161	-0.368	0.162	-0.369
Region 5	0.045	-0.207	0.047	-0.212
Region 6	0.060	-0.238	0.056	-0.230
Region 7	0.013	-0.113	0.072	-0.258
Region 8	0.034	-0.182	0.026	-0.159
Region 9	0.030	-0.170	0.030	-0.170
Region 10	0.052	-0.222	0.042	-0.202
Region 11	0.061	-0.240	0.065	-0.247
Region 12	0.031	-0.173	0.028	-0.166

Appendix C
Partial Linear and Linear Model Estimates

Variable	Partial Linear Model				Linear Model			
	1988		1995		1988		1995	
Experience					0.026	0.002	0.023	0.002
Experience squared					0.000	0.000	0.000	0.000
Schooling	0.045	0.003	0.049	0.003	0.063	0.003	0.068	0.003
Private	-0.156	0.025	-0.167	0.024	-0.125	0.021	-0.146	0.021
Marital status	0.285	0.017	0.276	0.015	0.130	0.018	0.114	0.017
Urbanity	0.047	0.064	0.042	0.069	0.057	0.016	0.054	0.016
PROF	0.372	0.029	0.400	0.028	0.345	0.025	0.392	0.025
ADMIN	0.571	0.055	0.183	0.041	0.593	0.046	0.144	0.036
CLERICAL	0.077	0.028	0.121	0.027	0.058	0.023	0.121	0.023
SALES	0.099	0.043	0.029	0.037	0.082	0.037	0.050	0.032
SERVICE	-0.105	0.027	-0.062	0.023	-0.075	0.023	-0.073	0.020
MINING	0.096	0.069	0.029	0.079	0.111	0.048	0.021	0.060
UTILS	0.159	0.053	0.085	0.055	0.050	0.045	0.098	0.049
CONST	0.074	0.029	0.068	0.026	-0.019	0.023	0.038	0.021
TRADE	-0.169	0.041	-0.152	0.034	-0.211	0.034	-0.198	0.030
TRANSPO	-0.065	0.025	-0.135	0.024	-0.172	0.020	-0.184	0.020
FIREBS	-0.016	0.037	-0.022	0.033	-0.073	0.031	-0.048	0.029
COMM	-0.098	0.027	-0.119	0.025	-0.188	0.022	-0.161	0.022
Region 1	-0.996	0.483	0.228	0.535	-0.200	0.030	-0.108	0.027
Region 2	-0.847	0.483	-0.088	0.523	-0.262	0.040	-0.186	0.038
Region 3	-0.303	0.467	0.159	0.543	-0.079	0.022	-0.100	0.023
Region 4	-0.325	0.420	-0.039	0.469	-0.100	0.020	-0.030	0.019
Region 5	-0.224	0.497	-0.294	0.552	-0.342	0.033	-0.369	0.031
Region 6	-0.697	0.502	-0.327	0.555	-0.330	0.029	-0.336	0.028
Region 7	-0.698	0.502	-0.247	0.557	-0.553	0.057	-0.351	0.026
Region 8	-0.587	0.484	-0.179	0.537	-0.432	0.037	-0.240	0.040
Region 9	-0.399	0.467	-0.088	0.525	-0.271	0.039	-0.306	0.037
Region 10	-0.507	0.498	-0.561	0.552	-0.220	0.031	-0.278	0.032
Region 11	-0.660	0.538	0.005	0.597	-0.262	0.028	-0.212	0.027
Region 12	-0.532	0.466	-0.237	0.517	-0.140	0.039	-0.231	0.038
Constant					1.232	0.048	1.271	0.046

Appendix D
Inequality Weights: Partially Linear and Linear Models

	Partially Linear Model			Linear Model		
	Inequality Share		Contribution to Change in Inequality	Inequality Share		Contribution to Change in Inequality
	1988	1995	1988-1995	1988	1995	1988-1995
Experience	0.009	0.007	-0.016	0.061	0.047	-0.021
Experience squared				-0.026	-0.019	0.018
Schooling	0.092	0.087	0.034	0.13	0.121	0.077
Private	0.022	0.02	-0.008	0.018	0.017	0.013
Marital Status	0.043	0.037	-0.02	0.02	0.015	-0.005
Urbanity	0.057	0.052	-0.016	0.007	0.005	-0.005
PROF	0.028	0.004	-0.001	0.053	0.051	0.041
ADMIN	0.002	0.005	-0.022	0.029	0.004	-0.125
CLERICAL	-0.001	0	0.011	0.002	0.005	0.02
SALES	0.005	0.003	0.013	-0.001	-0.001	-0.002
SERVICE	0	0	0.061	0.004	0.003	0.003
MINING	0.003	0.001	-0.002	0	0	-0.001
UTILS	-0.001	0	-0.017	0.001	0.001	0.002
CONST	0.006	0.006	0.001	0	0	-0.001
TRADE	0.006	0.011	-0.242	0.007	0.008	0.014
TRANSPO	0	-0.001	0.029	0.015	0.014	0.01
FIREBS	-0.008	-0.009	0.002	-0.002	-0.001	0.003
COMM	0.006	0.004	-0.019	-0.015	-0.012	0.006
Region 1	0.009	0.001	-0.081	0.002	-0.001	-0.013
Region 2	0.008	0	-0.084	0.003	0	-0.013
Region 3	0.001	-0.001	-0.025	0	0.001	0.004
Region 4	-0.001	-0.001	-0.009	0	-0.001	-0.005
Region 5	0.006	0.009	0.038	0.009	0.011	0.02
Region 6	0.016	0.008	-0.085	0.008	0.008	0.009
Region 7	0.009	0.011	0.032	0.007	0.016	0.059
Region 8	0.017	0.001	-0.168	0.013	0.002	-0.054
Region 9	0.006	0.001	-0.051	0.004	0.004	0.003
Region 10	0.004	0.007	0.038	0.002	0.003	0.012
Region 11	0.013	0	-0.138	0.005	0.003	-0.005
Region 12	-0.003	0.001	0.044	-0.001	0.001	0.012
Residual	0.645	0.737	1.701	0.646	0.693	0.925

Appendix E
Counterfactual Exercises: Partially Linear and Linear Models

	Partially Linear Model		Linear Model	
Variable	**Coefficient Effects**	**Characteristic Effects**	**Coefficient Effects**	**Characteristic Effects**
Experience	0.000	-0.002	-0.005	-0.007
Experience squared			0.003	0.004
Schooling	0.008	-0.014	0.009	-0.019
Private	0.020	0.020	0.002	-0.004
Marital Status	0.058	0.062	-0.002	-0.002
Urbanity	-0.022	-0.030	0.000	-0.002
PROF	0.046	0.045	0.006	-0.009
ADMIN	-0.005	-0.015	-0.011	-0.004
CLERICAL	-0.018	-0.001	0.003	0.001
SALES	0.001	0.000	0.000	0.000
SERVICE	0.008	0.004	0.000	0.000
MINING	0.000	0.000	0.000	0.000
UTILS	0.000	0.000	0.001	-0.001
CONST	0.000	0.001	0.000	0.001
TRADE	0.010	0.009	-0.001	0.002
TRANSPO	-0.003	-0.003	0.001	-0.002
FIREBS workers	0.001	0.004	0.001	0.000
COMM	-0.007	-0.007	0.002	0.001
Region 1	0.002	0.000	0.001	-0.002
Region 2	0.000	0.002	0.000	-0.002
Region 3	-0.008	-0.002	0.000	0.000
Region 4	0.009	-0.002	0.002	-0.001
Region 5	-0.001	0.008	0.001	0.001
Region 6	0.002	0.001	0.000	0.000
Region 7	-0.020	0.007	-0.009	0.011
Region 8	-0.004	-0.006	-0.001	-0.005
Region 9	-0.006	-0.002	0.000	-0.001
Region 10	0.002	0.006	0.001	0.001
Region 11	-0.008	-0.011	-0.001	-0.001
Region 12	-0.002	0.001	0.001	0.003
Residual	0.028	0.028	-0.004	0.036