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Three Essays on Robust Estimation of Key Factors Underlying the Changes to the U.S. Income Distribution

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Abstract

This dissertation consists of three chapters and mainly focuses on the robust estimation of different important factors contributing changes to the U.S. income inequality over the last two decades. The primary objective is to precisely estimate different labor market outcomes when the behaviors of the tails of the distribution bear much importance. These studies are very relevant in the current context of the U.S. labor market because over the last three decades the U.S. income distribution have come very skewed and therefore, we are more interested at the behaviors of the the upper and lower-tails of the U.S. income distribution compared to the middle.

The first chapter of the dissertation proposes a semi-parametric procedure to determine the contribution of human capital variables in explaining the changes of U.S. wage distribution function over the period of 1990-2000. The effects of these factors are estimated by using the Chamberlain's two stage Box-Cox quantile regression approach. One of the main contributions of this chapter is that it relaxes the linearity assumption of the conditional quantile function to estimate the counterfactual wage distribution function consistently. This chapter also shows that the proposed method provides better estimates of capturing the effects of human capital variables in the two tails of the U.S. wage distribution while the results of other parts of the distribution are comparable with the estimates of the previous study which used the linear quantile regression approach.

The second chapter proposes a semi-parametric estimation method known as 'Box-Cox Unconditional Quantile Regression' to explain the increasing trend of the U.S. wage inequality over the last two decades for men and women separately. Box-Cox Unconditional Quantile Regression is a generalization of the Linear Unconditional Quantile Regression model proposed by Firpo, Fortin and Lemieux (2009). The main contribution of this chapter is to determine the role of unionization in explaining the rising wage gap between the upper and lower tails of the U.S. wage distribution function during the period 1990-2010. I also show that proposed Box-Cox unconditional Quantile Regression model precisely estimates the pa-

rameters compared to the Linear Unconditional Quantile Regression model at the two tails of the U.S. wage distribution function while the results of the rest of the part of the distribution are comparable with the estimates of the previous study by Firpo et al. (2009). To summarize, this proposed approach is most applicable in cases where the behavior of the tails of the distribution bears much importance. I find that declining unionization can explain around 20-25 percent of the total fall in the 50/10 percentile wage gap and does not have much impact on the rise in the 90/50 percentile wage gap for men over the period 1990-2010. For women, unionization has very little impact on the rising wage gaps at different parts of the wage distribution over the last two decades.

In the third chapter I propose an extension of Rosen's (1986) theory of equalizing differences model by incorporating the role of different types of cognitive and noncognitive skills in worker's job preference function to explain the U.S. labor market sorting mechanism. I show that ignoring the impact of worker's skills on occupational choice decision leads to bias and inconsistent results because of sample selection specification error. This chapter proposes a solution of the problem by using workers' education level as the proxy of the cognitive skills. This chapter also tests the implication of the proposed labor market sorting model by using the current population survey and Occupational Information Network data sets and finds that a positive and statistically significant relationship exists between noncognitive skills and workers sorting behavior. The empirical results suggest that the relative employment share of women is higher in the occupation in which the people's task is more important because of their job preferences, which depend on the level of different types of noncognitive skills such as interpersonal and social skills. This type of sorting behavior can explain a large portion of the male-female wage gap.

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TABLE OF CONTENTS

LIST OF FIGURES

Figure

LIST OF TABLES

Table

CHAPTER I

Introduction

A large literature in labor economics investigates the widening of the U.S. wage structure over the last three decades (see Autor et al. 2008, Katz and Autor 1999, Bound and Johnson 1992). Many previous studies[1] in the income inequality literature have used canonical model to explain the changes in the U.S. wage inequality because the canonical model is not only elegant and conceptually attractive but it is also empirically successful. However, most recently many studies have showed that most of the action has been at the very top of the U.S. wage distribution function and canonical models fail to provide satisfactory results on explaining the upper and lower-tail wage inequality in the U.S. labor market over the last two decades.

One of the main motivations of my dissertation is to explain the asymmetric changes in the U.S. wage distribution with a steady rise in the upper-tail and a marginal fall in the lower-tail by using robust estimation methods. The proposed wage decomposition methods are more applicable when the behaviour of the tails of the distribution bears much importance. Alverdo et al. (2013) show that the driving force of the steep rise in the upper-tail wage inequality is due to the substantial increase of real wages in the upper-tail of the U.S. income distribution. Thus, proposed decomposition methods are relevant to explain the changes in the U.S. wage structure over the recent years.

[1]see Katz and Autor (1992), Autor, Katz and Krueger (1998), Autor, Katz and Kearney (2008) and Carnerio and Lee (2009), among many others.

The first chapter proposes a modified wage decomposition method to answer the question how much returns from education can explain the steep increases in wages in the upper-tail of the U.S. income distribution during the 1990s. Machado and Mata (2005) use the linear quantile regression method to construct a counterfactual wage distribution function. In this chapter, first I show that the linearity assumption of the conditional quantile function does not hold for U.S. Wage distribution data, especially at the upper-tail of the U.S. wage distribution function. Thus, Machado and Mata approach provides biased estimates of the decomposing terms. To solve this problem, this chapter proposes a modified wage decomposition method by using a flexible nonlinear quantile regression model, namely the Chamberlain Buchnisky Box-Cox model.

This chapter also shows that the estimated counterfactual distribution function converges to the true wage distribution function asymptotically. Proposed decomposition method results show that changes in the composition of the labor force play a secondary role, whereas the primary source of the asymmetric changes to the U.S. wage distribution during the 1990s is the changing labor market prices. I also show that the steep increase of the U.S. upper-tail wage inequality during the 1990s is not caused primarily by the heterogeneous returns from education.

The primary research question of the second chapter is why the income gap between the middle class and the poor fell over the last two decades. This fact in labor economics is also known as polarization of the U.S. economy. In labor economics there is a large literature which investigates why the high skilled workers are doing very well since 1980 by looking at the role factors such as, skilled biased technological changes, international trade etc. A large literature in both labor and public economics examines the role of different public transfer programs which are mainly targeted to the low skilled workers. Although the growth of real income for the middle class families has become almost stagnant over the last twenty years, there are not many studies attempts to explain the stagnation of the middle class families income.

The income gap between middle class and the poor is falling over the last two decades. This chapter provides an explanation of this fact by using the role of declining unionization. Unionization rate declined approximately one third for men and majority of those union workers are high school graduates. The hypothesis is middle class families average income fell because of this pattern of de-unionization. Current Population Survey (CPS) March outgoing rotation sample data for the period 1990-2010 is used to test this hypothesis. I have used 'Unconditional Quantile Regression' method to find out the effects of the declining unionization on wages for all the workers at each point of the income distribution; OLS or Quantile Regression estimates the effects of de-unionization for only union workers.

One of the main contributions is that this study has developed a variant of the Linear Unconditional Quantile Regression or a special form of the Nonlinear Unconditional Quantile Regression. This is build up from the first chapter which shows that the linear relationship between the dependent variable logarithm wages and unionization rate does not hold at different parts of the income distribution when the income distribution data are highly skewed. The proposed Nonlinear Unconditional Quantile Regression model finds out the impact of unionization on wages for all the workers in a robust way by constructing a counterfactual wage distribution function which is defined as union structure remains the same as in 1990 and all the other variables are distributed in 2010.

The effects of unionization at different parts of the income distribution are estimated by subtracting the counterfactual wage distribution function from the actual wage distribution. Estimated results suggest that declining unionization can explain approximately 20-25 percent changes of the 50/10 percentile wage gap for male over the last two decades and has no effect to the changes in female 50/10 percentile wage gap because there was not much change in female unionization rate over the last two decades. This question still remain unsolved in labor economics literature and this chapter provides a plausible explanation.

The third chapter investigates the question why the relative employment shares of women are higher in the occupations in which people's task is more important. The proposed labor market sorting model is an extension of the theory of equalizing differences proposed by Rosen (1986). In this framework, workers' job preferences not only depend on the job characteristics and monetary compensation, but also depend on workers' different types of cognitive and noncognitive skills; moreover, individuals vary in their stock of cognitive and noncognitive skills and jobs differ in terms of the task levels.

Labor market sorting behavior plays an important role to explain the trends of gender and racial wage gaps over the last two decades. Borghans, Weel and Weinberg (2006) investigate whether changes in the importance of the noncognitive skills can explain why women's wage increased more rapidly, while the wages of black grew more slowly over these years relative to earlier years in the U.S. labor market during the period of the late 1970s to the early 1990s.

Labor market sorting behavior plays an important role why does the male-female wage gap fall in the U.S. labor market over the last two decades, especially at the upper tail of the income distribution? However, during the same period the black-white wage gap remains steady. Borghans, Weel and Weinberg (2006) investigate whether changes in the importance of the noncognitive skills can explain during the period of the late 1970s to the early 1990s why women's wage increased more rapidly, while the wages of black grew more slowly over these years relative to earlier years in the U.S. labor market.

Proposed labor market sorting model is used by using the Occupational Information Network (O*NET) and CPS data. These data sets allow us to investigate which types of noncognitive skills have significant impact on different types of occupations. Additionally, this paper also shows the labor market sorting results by gender and race. There are two main contributions of this chapter in the labor market sorting literature. First, the proposed labor market model shows that without considering the impact of workers' cognitive and noncognitive skill levels on their occupational choice decisions leads to famous sample selection specification error. This study proposes a solution to this problem by using education levels as proxies of the workers' cognitive skills.

Estimated marginal effects of different types of noncognitive skills to choose occupations such as clerical and sales, and service with respect to the occupation professional, managerial and technical are almost always greater than 1 in a multinominal logit model. Although the relative magnitude of the coefficients varies a lot by race and gender, these results hold for different types of model specifications. Thus, workers' noncognitive skills can explain a large portion of the existing labor market sorting.

CHAPTER II

The Contribution of Human Capital Variables to Changes in the Wage Distribution Function

2.1 Introduction

Developing new decomposition methods to explain the changes in the wage distribution function has been an extensive research area for the last twenty years. The main reason for continued interest in this topic is that wage inequality in several countries, specifically in the United States, has increased sharply since the early 1980s. Autor et al. (2008) show that the slowing of the growth of overall wage inequality in the 1990s hides a divergence in the paths of upper-tail (90/50) and lower-tail (50/10) inequality. The upper-tail inequality has increased steadily since 1980, even adjusting for changes in the labor force composition; lower-tail inequality rose sharply in the first half of the 1980s and contracted thereafter. In this paper, I focus on the role human capital variables play in causing changes in the U.S. wage distribution function during the period of 1990 to 2000.

This paper proposes an extension of the decomposition method proposed by Machado and Mata (2005). The aim is to estimate a counterfactual distribution function F, which is of the form

$$F(w) = \int G(w|x)dH(x).$$

Here $G(\cdot)$ is the conditional Cumulative Distribution Function (CDF) of wage (w) given the covariates (X) in period $t = 0$ and H is the unconditional CDF of X in period $t = 1$. Machado and Mata (2005) estimate the inverse of G through a linear quantile regression model and estimate the integral through a simulation method. Machado and Mata (2005) point out that one of the limitations of their approach is that the linearity assumption of the conditional quantile function may be violated in many scenarios when applying real life data. This paper shows that the linearity assumption does not hold when $G(\cdot)$ is a very skewed distribution function.

Barsky et al. (2002) show that the Oaxaca-Blinder (1973) decomposition, based on the linear regression model, yields biased estimates of the decomposing terms when the underlying conditional expectation of Y given X is nonlinear. The Barsky et al. (2002) results can be extended in the quantile regression framework. This extension implies that the Machado and Mata (2005) approach gives consistent results only where the conditional quantile function is approximately linear.

In this paper, I suggest a flexible nonlinear quantile regression model for G, namely the Chamberlain Buchnisky Box-Cox model. The main reason for proposing this model is that the shape parameter in the Box-Cox model adjusts with each quantile of the wage distribution function to estimate the conditional quantile function. I also develop the formal asymptotic properties of the proposed decomposition method and apply the method by using U.S. labor market data for the period of 1990-2000 from the American Community Survey.

Recently, there have been several papers that have studied decomposition methods, including Chernozhukov et al. (2013a), Rothe (2010a, 2012a, b), Firpo et al. (2011, 2007), Antonczky et al. (2010), Altonji et al. (2008), Melly (2005), and DiNardo et al. (1996). (See also the extensive survey by Fortin, Lemieux, and Firpo (2011) on the wage decomposition literature.) These papers show how the function G mentioned above can be estimated by a wide range of parametric, semi-parametric or non-parametric methods.

DiNardo et al. (1996) analyze the effect of a change in the conditional distribution of a single covariate given the remaining ones (see also Donald et al. (2000) and Gosling et al.

(2000)). Hirano et al. (2003) and Firpo (2007, 2010) establish the efficiency of this estimation method. However, the DiNardo et al. (1996) method becomes practically infeasible when there are too many continuous variables. Moreover, re-weighting can have some undesirable properties in small samples when there is a problem of common support. Frolich (2004) finds that re-weighting estimators perform poorly in this context.

Rothe (2010a) proposes a fully non-parametric method to find the effect of an exogenous change in the distribution of covariates on the unconditional distribution of the outcome variable. In the wage decomposition literature, many researchers including Chernozhukov et al. (2013a), Firpo et al. (2011, 2007), and Machado and Mata (2005) propose parametric models. Using a correctly specified parametric model results in efficiency gains compared to the fully nonparametric method; however, such estimators are generally inconsistent when the parametric assumptions are violated.

Most recently, Rothe (2012a) measures the partial effect of a counterfactual change in the unconditional distribution of a single explanatory variable on some features of the unconditional distribution of Y in the context of a non-separable model. In a related paper, Firpo et al. (2009) estimate the impact of changing the distribution of explanatory variables X on the marginal quantiles of the dependent variable Y or other functionals of the marginal distribution of Y. By using either of the methods, one can directly calculate the distributional features. Firpo et al. (2009) identify their models only when X is exogenous. Rothe (2010b) estimates the unconditional partial effects in a nonseparable triangular model with endogenous regressors by using the control variable approach proposed by Imbens and Newey (2009).

Machado and Mata (2005) consider the effect of a change in the unconditional distribution of one of the covariates while holding constant the conditional distribution of the remaining covariates. Chernozhukov et al. (2013a) introduce the distributional regression model that corresponds to either changes in the distribution of the covariates, or changes in the conditional distribution of the outcome given covariates, or both. Chernozhukov et al. (2013a) argue that the distributional regression is an alternative to quantile regression. Thus, both the approaches provide similar results when the support of X is sufficiently rich.

Chernozhukov et al. (2013a) point out that Machado and Mata's (2005) method works well if Y has a smooth conditional density and may provide a poor approximation of the conditional distribution function when Y is discrete or consists of mass points. In contrast, distributional regression does not require smoothness of the conditional density because the approximation is done point-wise in the threshold Y, and thus handles continuous, discrete, or mixed Y without any special adjustment.

This paper contributes to the previous literature by developing a flexible decomposition method to analyze the differences in the distribution of individuals' economic outcomes across two countries, time periods or subgroups of the population. In particular, the results can be used to make inference on the change of the distribution function as a whole, its moments, quantiles, and inequality measures such as the Lorenz curve or Gini coefficient. I also show that the estimated counterfactual distribution function of the proposed method converges to the true distribution function asymptotically. This asymptotical property of the proposed decomposition method establishes the validity of the inference procedure.

The empirical contribution of this paper is that the proposed decomposition method can precisely estimate the contribution of human capital variables especially in the two tails of the wage distribution function. In comparison with the proposed decomposition method results, I find that the Machado and Mata (2005) approach underestimates the price effects of labor market in the lower-tail and overestimates in the upper-tail of the U.S. wage distribution function for the period 1990-2000. Differences in the rest of the parts of the wage distribution function are not statistically significant.

The proposed decomposition method results show that there is a steady rise in upper-tail wage inequality and a flat or declining lower-tail wage inequality during the 1990s. The results are consistent with Autor et al. (2008). Autor et al. (2005) called this phenomena the 'polarization' of the U.S. labor market, with a particularly strong market for workers in the top parts of the skill distribution and, at the same time a deterioration in market conditions for workers in the middle, and reasonably steady market conditions for those near the bottom.

The structure of the paper is as follows. Section 2 describes the econometric model, the construction of the counterfactual wage distribution function, and the decomposition of the wage distribution function. In section 3, I discuss the data, show the empirical results and also compare the results with the conventional wisdom of the wage inequality literature. I conclude in section 4. All the proofs are shown in the Appendix.

2.2 Econometric Model

The Mincer equation is the most widely used specification of the empirical earnings equation in the labor economics literature. This equation is typically specified in the linear functional form. A more general approach would be not to constrain the model to linear form but rather to let the data determine the exact transformation that results in a linear relationship between the dependent variable and the covariates. Box-Cox (1964) suggests such a model in a nonlinear set up.

2.2.1 Model Set Up

The econometric model I use in this paper specifies that the τth conditional quantile of w (wage), given x ($Quant_\tau(w|x)$), depends on a linear index, $x'\beta_\tau$, through a nonlinear function $g(\cdot)$, that is,

$$Quant_\tau(w|x) = g(x'\beta_\tau, \lambda_\tau) \tag{2.1}$$

where $g(\cdot)$ is strictly monotonically increasing in $x'\beta_\tau$ and also depends upon the parameter λ_τ. Moreover, $w > 0$, $x \in \mathbb{R}^k$ are observed, while the parameters $\beta_\tau \in \mathcal{B} \in \mathbb{R}^k$ and $\lambda_\tau \in \mathbb{R}$ are unknown and $\tau \in (0, 1)$.

The specification of model (1) is quite flexible because it depends on the linear index $x'\beta_\tau$ and allows the whole transformation to change for each different quantile $\tau \in (0, 1)$. Powell (1991) shows the Box-Cox (1964) transformation can be estimated in a nonlinear quantile regression framework.

In the Box-Cox transformation, the inverse of $g(x'\beta_\tau, \lambda_\tau)$ is given by

$$w_\lambda = g^{-1}(w, \lambda) = \begin{cases} (w^\lambda - 1)/\lambda & if \;\; \lambda \neq 0 \\ log(w) & if \;\; \lambda = 0, \end{cases} \tag{2.2}$$

assuming $\lambda \in \mathbb{R}$ and $\mathbb{R} = [\underline{\lambda}, \bar{\lambda}]$ to be a finite closed interval. The advantage of using the Box-Cox transformation is that it preserves the ordering of the observation due to the equivariance property of quantiles with respect to the monotonically increasing w_λ. Therefore,

$$Quant_\tau(w_\lambda|x) = g^{-1}\left(Quant_\tau(w|x)\right). \tag{2.3}$$

Using the Box-Cox transformation as the inverse of $g(x'\beta_\tau, \lambda_\tau)$, equation (1) becomes

$$Quant_\tau(w|x) = \left(\lambda_\tau Quant_\tau(w_\lambda|x) + 1\right)^{1/\lambda_\tau} \tag{2.4}$$

Buchinsky (1995) shows that the Box-Cox transformation specified in (2) satisfies the property

$$Quant_\tau(w_\lambda|x) = x'\beta_\tau. \tag{2.5}$$

By using the equations (4) and (5), the conditional quantile function of w given x becomes

$$Quant_\tau(w|x) = \left(\lambda_\tau x'\beta_\tau + 1\right)^{1/\lambda_\tau}. \tag{2.6}$$

Note that the conditional quantile function, $Quant_\tau(w|x)$ becomes linear when $\lambda_\tau = 1$.

The estimation of β_τ and λ_τ is studied by Powell (1991), Chamberlain (1994), Buchinsky (1995) and Fitzenberger et al. (2010). Box-Cox quantile regression minimizes the distance function

$$\underset{\beta_\tau \in \mathcal{B}, \lambda_\tau \in \mathbb{R}}{min} \ \frac{1}{n}\sum_{i=1}^{n} \rho_\tau \left(w_i - (\lambda_\tau x_i' \beta_\tau + 1)\right)^{1/\lambda_\tau}, \tag{2.7}$$

where the loss function is given by $\rho_\tau(u) = \tau|u|\mathbb{I}_{u\geq 0} + (1-\tau)|u|\mathbb{I}_{u<0}$ and $\mathbb{I}$ denotes the indicator function. Powell (1991) shows that these nonlinear estimators $\hat{\lambda}_\tau$ and $\hat{\beta}_\tau$ are consistent and asymptotically normal.

2.2.2 Chamberlain Buchinsky Two Step (CBTS) Estimation

Chamberlain (1994) and Buchinsky (1995) suggest the following two step procedure which exploits the equi-variance property of quantiles:

Step 1: Estimate $\beta_\tau(\lambda_\tau)$ conditional on λ_τ by

$$\hat{\beta}_\tau(\lambda_\tau) = arg \underset{\beta_\tau \in \mathcal{B}}{min} \ \frac{1}{n}\sum_{i=1}^{n} \rho_\tau \left(w_{\lambda_i} - x_i' \beta_\tau\right) \tag{2.8}$$

Step 2: Estimate λ_τ by solving

$$\underset{\lambda_\tau \in \mathbb{R}}{min} \ \frac{1}{n}\sum_{i=1}^{n} \rho_\tau \left(w_i - (\lambda_\tau x_i' \hat{\beta}_\tau(\lambda_\tau) + 1)^{1/\lambda_\tau}\right) \tag{2.9}$$

Chamberlain (1994) shows the asymptotic distribution of the CBTS estimators. Buchinsky (1995) derives large sample properties of this estimator for discrete regressors when applying the minimum distance method.

Fitzenberger et al. (2010) address a numerical problem for implementing the CBTS estimation method. They argue that the estimation problem given in (9) can only be solved if

$$\lambda_\tau x_i'\hat{\beta}_\tau(\hat{\lambda}_\tau) + 1 > 0 \tag{2.10}$$

for all $i = 1, 2, ..., n$ and for all $\lambda_\tau \in \mathbb{R}$. Fitzenberger et al. (2010) suggest to solve this problem by incorporating a indicator function in the second step of the estimation. The indicator function takes a constant value whenever the condition in (10) fails to satisfy. This modification guarantees that the objective function is a well defined sum from 1 to n. Fitzenberger et al. (2010) show that the modified estimator has similar asymptotic properties to the original CBTS estimator.

2.2.3 Test for Box-Cox Conditional Distribution Model

In this subsection, I test the correct specification of the conditional distribution model using the Generalized Conditional Cramer-von Mises (GCCM) test proposed by Rothe and Wied (2013). Let $\mathcal{F}$ be the class of all conditional distribution functions on the support of Y given X that satisfy all the regularity conditions shown by Rothe and Wied (2013). We consider a parametric family

$$\mathcal{F}^0 = \{F^{-1}(\tau|x) = g(x'\beta_\tau, \lambda_\tau) \;\; for \;\; some \;\; \theta \in \mathcal{B}(\tau, \Theta)\} \in \mathcal{F} \quad \forall \;\; \tau \in (0, 1)$$

.

The hypothesis Rothe and Wied (2013) propose to test is that $\mathcal{F}$ coincides with an element of $\mathcal{F}^0$.

$$H_0 : F(y|x) = F(y|x, \theta_0) \;\; for \;\; all \;\; (y, x) \in \mathbb{R}^{k+1}$$
$$H_1 : F(y|x) \neq F(y|x, \theta_0) \;\; for \;\; some \;\; (y, x) \in \mathbb{R}^{k+1}$$

The test statistics T_n and the bootstrap α critical values $\hat{c}_n(\alpha)$ have been computed by following the procedure shown by Rothe and Wied (2013) where $\hat{c}_n(\alpha)$ is the smallest constant that satisfies

$$P_b(T_{b,n} \leq \hat{c}_n(\alpha)) \geq 1-\alpha,$$

and P_b is the probability with respect to bootstrap sampling and $T_{b,n}$ is the bootstrap test statistics. Rothe and Wied (2013) test rejects H_0 if $T_n > \hat{c}_n(\alpha)$ for some pre-specified significance level $\alpha \in (0,1)$.

2.2.4 Counterfactual Wage Distribution Function

I use CBTS estimators to construct the counterfactual wage distribution. The steps are as follows:

1. Draw random sample of size m from $\tau \in (0,1) : \tau_1, ..., \tau_m$.

2. For each $\tau \in (0,1)$, using the CBTS estimators, estimate the following conditional quantile function

$$\begin{aligned}\hat{Q}_{g,\tau} &= g(x'\hat{\beta}_\tau, \hat{\lambda}_\tau) \\ &= \left(\hat{\lambda}_\tau x_t'\hat{\beta}_\tau + 1\right)^{1/\hat{\lambda}_\tau}.\end{aligned}$$

3. Use the estimated result to draw a random sample from $\{w^i_{t=1}\}^m_{i=1}$, $\{w^i_{t=0}\}^m_{i=1}$ and $\left\{w^{c,i}_{t=1}\right\}^m_{i=1}$ where

$$\begin{aligned}\left\{w^i_t\right\}^m_{i=1} &= F^{-1}_{w_t|x_t}(\tau_i, x_t) = g((x^i_t)'\hat{\beta}_\tau, \hat{\lambda}_\tau); \quad t = 0, 1 \\ \left\{w^{c,i}_{t=1}\right\}^m_{i=1} &= F^{-1}_{w_{t=1}|x_{t=1}}\left(F_{w_{t=0}|x_{t=0}}(w_{t=0}, x_{t=0}), x_{t=0}\right).\end{aligned}$$

Here $w^{c,i}_{t=1}$ denotes the ith draw from the counterfactual wage distribution function. $F^{-1}_{w_t|x_t}(\tau_i, x_t)$

are the τ_ith conditional quantile functions for the periods $t = 0, 1$. $F^{-1}_{w_{t=1}|x_{t=1}}(\cdot)$ is the τ_ith counterfactual conditional quantile function.

The counterfactual wage distribution function consists of two parts. The first operator $F^{-1}_{w_{t=1}|x_{t=1}}$ ensures that the market return of the covariates remains fixed at period $t = 1$ whereas the second part $\big(F_{w_{t=0}|x_{t=0}}(w_{t=0}, x_{t=0}), x_{t=0}\big)$ implies that the distribution of covariates remains constant at period $t = 0$.

2.2.5 Decomposition of Changes in Wage Distribution

The main objective of constructing a counterfactual wage distribution function is to use it to decompose differences in distributions. I use the extended Oaxaxa (1973) decomposition method like DiNardo et al. (1996), Machado and Mata (2005), and Firpo et al. (2007, 2011) to decompose the differences in distribution of wages in the years 1990 and 2000.

The main analysis of changes in the distribution functions of wage between the period $t = 0$ (year 1990) to period $t = 1$ (year 2000) is as follows:

$$F(w_{t=1}) - F(w_{t=0}) = \underbrace{[F(w_{t=1}) - F(w_{t=1}; x_{t=0})]}_{\text{Composition Effect}} + \underbrace{[F(w_{t=1}; x_{t=0}) - F(w_{t=0})]}_{\text{Wage Structure Effect}} + Residual$$

The first bracket represents the effect of changes in the distribution of covariates which is denoted as the composition effect. The second bracket represents the effect of changes in the market returns of the human capital variables which we call the wage structure effect, and the rest is called the residual effect. The advantage of this decomposition is that we can decompose all the standard summary measures such as Gini coefficients, Theil coefficients, skewness etc., since we can estimate the whole counterfactual distribution function.

Similarly, we can also measure the impact of individual covariates ($\tilde{x}_t$) by considering the following equation

$$Impact\ of\ \tilde{x}_t \equiv F(w_{t=1}) - F\left(w_{t=1}; x'_{t=1}, x_{t=0}\right),$$

where $x_t = [\tilde{x}_t | x'_t]$ and x'_t are all the other covariates except $\tilde{x}_t$. The counterfactual distribution function $F\left(w_{t=1}; x'_{t=1}, x_{t=0}\right)$ can be recovered from $F(w_{t=1}; x_{t=0})$ by assuming $\tilde{x}_t \in x_t$ follows independent distribution.

The independence assumption allows us to write the joint distribution of the covariates as the product of the marginal distributions. The assumption may not hold in different scenarios. However, we can relax this assumption and estimate $F\left(w_{t=1}; x'_{t=1}, x_{t=0}\right)$ by using either the fully non-parametric or the spline method. The tradeoff is a relatively small marginal efficiency gain at the cost of computational complexity.

This decomposition is quite attractive since the measurement of the impact does not depend on the ordering, unlike the DiNardo et al. (1996) method. Autor et al. (2005) show that this decomposition provides a precise link between the 'full variance accounting' technique for analyzing inequality introduced by Juhn et al. (1993) and the kernel re-wighting proposed by DiNardo et al. (1996). However, Rothe (2012b) points out that most of the previous decomposition methods, including Machado and Mata (2005), are not additive in the sense that the sum of the effects of all individual covariates is not equal to the effect of changing all covariates.

The preciseness of the estimated impact of human capital variables of the proposed method depends on the total number of quantiles at which we estimate the conditional quantile function. In this paper, I take 3,000 quantiles between 0 and 1 to construct the unconditional wage distribution function. Theoretically, the more quantiles the better, but one of the drawbacks of the proposed decomposition method is that it is computational intensive and the computational time is greater compared to the simulation method introduced by Machado and Mata (2005).

2.2.6 Asymptotic Properties of the Decomposition Method

I show the following two asymptotic properties of the proposed decomposition method. The proofs of the properties are shown in the appendix.

(i) Complete Mappings: Assume that the conditional cumulative distribution function of w_t given x_t, $F_{w_t|x_t}(w_t|x_t)$, is monotonically increasing over the domain of $w_t \in \mathcal{W}_t$ and $\mathcal{W}_t$ is closed and bounded in $\mathbb{R}^k$ for $t = 0$ and 1, where k is the row dimension of $\mathcal{W}_t$. Then we have

$$F(w_t) \equiv \left\{ F^{-1}_{w_t|x_t}(\tau_i) \right\}_i^m \quad as \;\; m \to \infty,$$

where m is the number of draws.

(ii) Convergence in Distribution: Let $\hat{\theta}^c$ be the quantile estimator that minimizes the counterfactual conditional quantile function of w given x, $g^c(\theta^c)$. We define a random variable $Y = g(x'_{t=0}\beta_\tau^{t=1}, \lambda_\tau^{t=0})$ and assume that the distribution function of Y, $F(x'_{t=0}\beta_\tau^{t=1}, \lambda_{t=0})$ exists. Let $\hat{Y}_n = g_n(x'_{t=0}\hat{\beta}_\tau^{t=1}, \hat{\lambda}_\tau^{t=0})$ have a distribution function $F_n(\cdot)$ for each n. Then, under the regularity conditions as shown by Powell (1991), we obtain

$$F_n(\hat{Y}_n) \xrightarrow{d} F(Y) \quad as \;\; n \to \infty.$$

2.3 Data and Results

The data are drawn 1 percent self weighted 1990 and 2000 samples from the American Community Survey. The data consists of U.S.-born black and white men aged 40-49 with at least five years of education, positive annual earnings and hours worked in the year preceding the census, and a nonzero sampling weight. The wage measure used is a weekly wage measure computed by dividing the annual earnings by the number of weeks worked in the previous year. I have restricted my sample sizes to 30,000 for both the years 1990 and 2000 to reduce the computational time for the simulation method used in the empirical analysis. The regressors consist of years of schooling and other basic controls[1]. Potential experience for men has been calculated by subtracting 6 and number of schooling years from the age variable.

Table 1 shows between group changes in wages and labor force composition in the samples 1990-2000 for groups defined by education, potential experience and race. The third column indicates that there are about 1 to 2 percent more high school, some college and college graduates and 2 to 3 percent less high school drop out and post college graduate workers in the year 2000 compared to 1990. These differences imply that although the average education level remain almost the same over the period 1990 to 2000, the relative fraction of the low skilled workers has decreased. The sixth column indicates that the average racial wage gap has fallen approximately 2 percent in our samples.

In Table 2, I report the empirical rejection probabilities from n replications of the simulation process discussed by Rothe and Wied (2013), where the values of n are 50, 100, and 200. We see that for the year 2000, the linear quantile regression model leads to an adequate fit of the conditional male wage distribution data becuase we reject the null hypothesis of linear specification. We also note that the linear quantile regression model rejection rates are always higher than the Box-Cox quantile regression models at both 10 percent and 5 percent critical levels. This implies that the linear quantile regression model specification used in the empirical analysis is not the best model specification for our sample data.

Rothe and Wied (2013) point out that rejection of the null hypothesis does not directly imply that such specifications result misleading conclusions. However, for large samples Rothe and Wied (2013) argue that the Generalized Conditional Cramer-von Mises (GCCM) test is able to pick up deviations from the null hypothesis even if they are not economically significant magnitude. Thus, by using the Box-Cox Quantile Regression model we can obtain

[1] In the regressors, I have excluded various determinants of earnings such as tenure and occupation dummies because these variables are potentially endogenous and determined by education itself (Angrist and Pischke (2009)). Annual income is expressed in 1989 dollars using the Personal Consumption Expenditures Price Index.

more precise results at those quantiles of the wage distribution function for which the linearity assumption in parameters is a poor approximation of the conditional quantile function. Moreover, the linear and log-linear Quantile Regression models are special cases of the Box-Cox Quantile Regression model.

2.3.1 Overall Changes in Wage Distribution

The top part of Figure 1 shows how the probability density function changes from 1990 to 2000 and the bottom panel shows the same for the U.S. wage distribution function. We see that the area under the wage density curve of the upper-tail in 2000 is greater in comparison to 1990. This difference implies that the employment opportunities for the high-skill workers has gone up compared to the moderately and low skilled workers during the 1990s in the U.S. labor market. The result is in line with the Autor et al. (1998) findings on relative demand growth for the high-skill workers during the 1990s.[2]

The bottom part of Figure 1 represents the fraction of workers' wage less than a given wage. By comparing the cumulative distribution functions of both the years, we see that employment shares of the very low and high skilled workers increased while employment shares for the moderately skilled workers contracted during the 1990s. Firpo, Fortin and Lemieux (2011) argue that the recent changes in task-based occupational structure play a very important role to explain this phenomenon. Acemoglu and Autor (2010) propose a task-based framework for analyzing the allocation of skills to task for studying the effect of new technologies on the labor market and their impact on the distribution of earnings.

Table 3 shows the changes in the estimated unconditional wage distribution by using both the Quantile Regression and the Box-Cox Quantile Regression simulation methods. In the seventh row, the term 'Scale' refers to the percentage change in the wage gap between the 75th quantile and 25th quantile. The random samples from the wage distribution functions

[2]Card and DiNardo (2002), Autor, Levy and Murnane (2003) emphasize more on the role of Skill Biased Technological Changes (SBTC) in the US wage structure.

have been generated through the steps described in Section 2, with the number of replications equal to 3,000. The numbers in the parentheses indicate the 95 percent bootstrap confidence interval which has been generated by 1,000 replications.

By comparing the third and sixth columns of Table 3, we note that the linear quantile regression and the Box-Cox quantile regression models give us statistically different results in the upper-tail of the male wage distribution. Proposed decomposition method estimates the changes in wages as 9 to 23 percent in the upper-tail of the U.S. wage distribution function while the Machado and Mata (2005) method estimates are 1 to 7 percent. However, both Machado and Mata's (2005) decomposition method and proposed approach show that there are marginal changes in wages in the lower-tail. This difference at the upper-tail is because the linearity assumption in the parameters of the conditional quantile function is unable to capture the precise changes in the upper-tail of a very skewed wage distribution function.

Our results on U.S. wage inequality are qualitatively similar to Autor et al. (2008), Goos and Manning (2003) and Autor, Levy and Murnane (2003). This pattern of changes in the U.S. wage distribution in the 1990s differs sharply compared to the 1980s, with more rapid growth of real wages at the top of the wage distribution relative to the middle and the bottom of the wage distribution. Goos and Manning (2003) and Autor, Katz and Kearney (2005) characterize this pattern as the polarization of the U.S. labor market. This pattern suggests a central role for labor demand shifts in explaining changes in the U.S. wage distribution function during the 1990s.

2.3.2 Decomposition Method Results

In Table 4, the wage distribution function has been decomposed into three parts, namely composition effect, wage structure effect and residual effect. Row by row, I report the estimates of these three effects for different quantiles and various inequality measures. Proposed decomposition method results show that the wage structure effects are roughly 1.5 to 2 times larger than the composition effects. These results suggest that during the 1990s, the primary source of changes in the wage distribution is the wage structure effect. The composition effect plays a very minor role.

The residual effect is defined as the unexplained part of the change in the wage distribution as shown in Table 3. By comparing the third and sixth columns of Table 4, we note that the residuals from the proposed method are smaller than those from the Machado and Mata (2005) method for all parts of the distribution except the region around the median. The results in Table 4 are consistent with the properties of the Quantile Regression estimators. The linear Quantile Regression provides the best estimators when the conditional quantile function is linear. Angrist et al. (2006) show that Quantile Regression gives the minimum mean-squared error linear approximation to the conditional quantile function even when the linear model is misspecified. Buchnisky (1995) gets similar results like ours by using Minimum Distance (MD) estimators for the Box-Cox Quantile Regression model.

The results of Table 3 and Table 4 have been summarized in Figure 2. The top left panel of Figure 2 shows that the gaps between the estimated changes in wages for the linear and nonlinear Quantile Regression approaches increase in the higher quantiles of the wage distribution function. The residual effects have been shown in the bottom right panel. As shown, the absolute values of the residuals of the nonlinear Quantile Regression approach are significantly in the two tails of the wage distribution compared to the residuals from the linear Quantile Regression approach introduced by Machado and Mata (2005).

This can be explained by using the other three subplots of Figure 2. The top right and bottom left panels show that the composition effects are similar in both methods but the absolute values of wage structure effects from the linear Quantile Regression approach are higher compared to the proposed Box-Cox Quantile Regression method at the two tails. Since the linear Quantile Regression method underestimates the changes in wages in the upper-tail and marginally overestimates in the lower tail of the distribution, the absolute values of the residuals are higher at the two tails of the distribution compared to the proposed wage decomposition method.

The next part of the decomposition measures the impact of individual workers' characteristics such as education, experience and race. This extended Oaxaca decomposition method takes care of the unobserved heterogeneity in returns to education (Henderson et al. 2011) by assuming the distribution of unobserved skills remains the same over the two time period we consider. Thus by using this type of decomposition method, we can only compare similar types of workers in two time periods. Alternatively one can use the Instrumental Variable Quantile Regression (IVQR) approach proposed by Chernozhukov and Hansen (2006, 2008, 2013b) to address the unobserved heterogeneity issue. Although the IVQR method has been applied in many research fields, it is rather new to the human capital variables literature[3].

The second column of Table 5 shows that had the distribution of education remain the same as in 1990, then the 90/50 percentile wage gap would have increased by 4.2 percent. The inequality increasing effect of education is directly driven by the increase of the estimated effects for education in the upper tail of the wage distribution. The impact of race does not have much contribution to the changes in wage distribution function. The fifth column shows that the residuals contribute approximately 8 to 13 percent of the total changes in the U.S. wage distribution during the 1990s. Melly (2005) and Lemieux (2006) both find that residual factors account for about 20 percent of the increase in wage inequality during the period 1973 to 1989.

2.3.3 Discussion

It is important to see how the results of our proposed decomposition method compare with the conventional wisdom of the existing wage inequality literature. Our results suggest that the dominating factor of the recent changes in the U.S. wage inequality is the wage structure effect. Machado and Mata (2005), Autor et al. (2005, 2008) and Firpo, Fotin and Lemieux (2011) apply different decomposition methods to different data sets but obtain similar results. Another finding of this paper is that had the distribution of labor force

[3] Wang (2013) and Arabsheibani and Staneva (2012) used IVQR method to find out heterogeneous returns to education.

remained the same as in 1990, the 90/50 wage gap would have increased roughly by 16 percent [4] and our estimated effects of returns to education can explain only one fourth of this change. Buchnisky (1994) shows that the differences of returns to education have increased from 0.73 to 2.32 percent over the period 1978 to 1987. Katz and Murphy (1992) find that college wage premium compared to the high school graduate has increased approximately 2.6 percent per annum during the period 1963-1987.

For a direct comparison with the results of Autor et al. (2008), I have used their same data to explain the trends in U.S. wage inequality over the period 1963-2005[5]. Table 6 represents regression models for the overall college high school wage gaps following the specifications proposed by Autor et al. (2008). In addition, I add quantile regression estimates for the 10th, 50th and 90th quantiles[6]. Models 3 and 4 consider linear time trends along with the college high school relative supply, real minimum wage and male prime-age unemployment rate whereas models 1 and 2 allow more flexible time trends by incorporating quadratic and cubic functions. By comparing the first and third columns of the four different specifications, we note that OLS estimates are very similar to the median regression.

The quantile regression estimates from the four specifications suggest that the range of the college wage premium estimates is 1.5 to 3.3 percent per annum from the lower-tail to the upper-tail of the wage distribution. The OLS estimates of the relative supply measures are significantly different from the quantile regression estimates at the two tails of the wage distribution. The Quantile Regression estimated elasticity of substitution between high school and college graduate workers varies over the range 1.07(1/0.93) to -1.82(1/-0.54) from the lower-tail to upper-tail of the wage distribution. These estimated elasticity of substitution between high school and college graduate workers can not explain the changes in the upper-tail wage inequality and this is consistent with Autor et al. (2008) since they also argue that the two-factor CES model fails to provide an adequate explanation of the

[4]The difference between the fifth and third row of wage structure effect at Table 4.

[5]See Table 1 in Autor et al. (2008) for descriptive statistics and appendix for data preparation details.

[6]I do not include nonlinear quantile regression estimates because the nonlinear quantile regression estimates from the statitical software 'R' are infeasible for 43 observations.

evolution between wage inequality since the early 1990s.

Table 7 shows the regression and quantile regression models for the college high school wage gaps by overall and four different experience groups. The inverse of the aggregate supply coefficient represents the aggregate elasticity of substitution; similarly, inverse of the coefficients for the first row show the partial elasticity of substitution between different experience groups within the same education group. Consistent with Autor et al. (2008), the quantile regression estimates also suggest that there are substantial effects of both own group and aggregate supplies on the evaluation of the college wage premium by experience groups.

Autor et al. (2008) find that aggregate elasticity of substitution in Table 7 models are very similar to the aggregate models in Table 6 which is also true in the upper-tail of the wage distribution, shown in the 4th and 8th column. However, in the lower tail, the values of the aggregate elasticity of substitution are significantly different in Table 6 and Table 7. This implies that the return to college for the low-experienced workers is different compared to the medium-experienced (20-29 years) and older workers (30-39 years). The partial elasticity of substitution between experience groups is very consistent across the wage distribution and similar to the OLS estimate of 3.55 as shown by Autor et al. (2008). The lower panel shows that the OLS and median regression estimates are very similar for the four experience groups.

Table 8 summarizes the overall and residual inequality over the period 1963-2005 by using the proposed counterfactual wage decomposition method. For the counterfactual analysis, Autor et al. (2008) use a model which consists of 95 dummy variables: full set of age dummies, dummies for nine discrete schooling categories, and a full set of interactions among the schooling dummies and a quartic in age and no continuous variable. I do not use the same covariates as used by Autor et al. (2008) to avoid the computational complexity of the interior point algorithms for quantile regression as discussed by Koenker (2005)[7]; rather I

[7]See Roger Koenker (2005) 'Quantile Regression' for detailed discussion. Standard statistical softwares

follow the same specification used in the main empirical analysis for consistency. To construct the counterfactual wage distribution function by using the simulation method as described in Section 2, I use 5,000 replications. The numbers in Table 4 represent the effects of labor market prices on the overall earnings inequality while holding labor force composition at the base years 1973, 1989 and 2005.

For comparison with Autor et al. (2008), we begin by discussing the overall wage inequality. The upper panel of Table 4 shows that the male 90/50 percentile wage gap (upper-tail wage inequality) rose during both halves of the sample by 10.3 percent from 1973 to 1989 and 15.4 percent from 1989 to 2005. We note that the price effects can explain almost all changes in the upper-tail wage inequality. For females, the 90/50 percentile wage gap rose by 11 percent between 1973 to 1989 and 12.9 percent between 1989 to 2005. Again holding labor force composition constant at its 1973, 1989 and 2005 levels gives us results similar to the men. The middle and bottom panels of Table 8 show the price effects for 50/10 and 90/10 percentile wage gaps for both men and women. These results suggest that the basic message, price effect dominates the composition effect, does not change for both men and women over the period 1973-2005.

Autor et al. (2008) conclude that "Changes in labor force composition do not substantially contribute to an explanation for the diverging path of upper and lower-tail inequality, either overall or residual, over the past three decades". As shown in Table 8, our findings are qualitatively similar with the conclusions of Autor et al. (2008) although we use a simpler model specification and a different counterfactual decomposition method to obtain the price effects and composition effects. For residual inequality, I find that for the period 1989-2005, in most of the cases price effects are the dominating factors for changing in residual wage inequality which is consistent with Autor et al. (2008). However for the period 1973-1989, I find that although price effect plays a significant role to changes in residual wage inequality, it is not the dominating factor as suggested by Autor et al. (2008).

fail to provide quantile regression estimates for the models which have too many dummy variables.

To conclude, Autor et al. (2008) use a structural model and college wage premium compared to high school graduate as a measure of returns to education whereas this paper uses a canonical Mincer earnings equation and constructs a counterfactual wage distribution function to estimate the returns from human capital variables. However, the results from the main empirical application and comparison with Autor et al. (2008) demonstrate that although the relative magnitudes of the price effects from the proposed method are higher in some cases, especially for the wage gap between the two tails of the distribution, these results are qualitatively similar. Our results find even stronger price effects for the overall wage inequality compared to Autor et al. (2008) especially for the 90/10 percentile wage gap; however, the main conclusion remains the same. Autor et al. (2008) point out that their counterfactual analysis depends on the partial equilibrium assumption that prices and quantities are independent which is precisely to the opposite spirit of the supply-demand analysis; the proposed method does not require such a strong economically unappealing assumption.

2.4 Conclusion

This paper proposes a modified wage decomposition method based on a very popular approach proposed by Machado and Mata (2005). First, I show that the linearity assumption of the conditional quantile function does not hold for the U.S. male wage distribution data at the year 2000 by using the Generalized Conditional Cramer-von Mises (GCCM) test proposed by Rothe and Wied (2013). To overcome this linearity issue, I use the Chamberlain Buchinsky Two Step Box-Cox Quantile Regression method. The advantage of this method over the linear quantile regression method is that the shape parameter of the Box-Cox transformation adjusts with each quantile of the wage distribution to capture the nonlinear shape of the conditional quantile function.

This paper also shows that the estimated counterfactual distribution function by using the Box-Cox Quantile Regression method converges to the true distribution function asymptotically. This asymptotic property ensures the validity of the inferences based on the decomposition method results. By using the re-sampling procedure, I also show that theoretically we can fully recover the unconditional wage distribution function. This implies that we need a large number of draws to construct a counterfactual wage distribution function. I have used 3,000 draws for the empirical analysis and 5,000 draws for the comparison results with Autor et al. (2008).

This paper also implements the proposed decomposition method to determine the impact of human capital variables that contribute to changes in the male wage distribution function over the period 1990-2000. Proposed decomposition method results show that changes in the labor force composition do not contribute an explanation for the steep rise in wages at the upper-tail of the U.S. wage distribution during the 1990s. This result is consistent with Autor et al. (2008) who used a variant of DiNardo, Fortin and Lemieux (1996) wage decomposition method for the period 1963-2005. In addition, this paper also shows that returns from education can explain only a small fraction of the total changes in wages in the upper tail of the wage distribution and do not explain why the lower tail wage inequality fell during the 1990s. Thus, return from schooling is not the primary source of recent divergence of upper-tail and lower-tail wage inequality in the U.S. labor market.

The sources of the asymmetric changes in the U.S. wage distribution with a steady rise in the upper-tail and a marginal fall in the lower-tail during the 1990s still remain unresolved. Autor et al. (2008) show that hypotheses such as falling minimum wages, relative demand growth for more skilled workers and skill biased technological change fail to fully explain the upper-tail inequality paired with declining lower-tail inequality. Firpo, Fortin and Lemieux (2011) use unconditional quantile regression method to explain the changes in the U.S. wage structure over the last three decades by looking at the roles of skilled biased technological changes and job offshorability. Katz and Murphy (1992) and Autor, Katz and Krueger (1998) propose an explanation based on relative demand growth for high skilled workers and fluctuations in relative skill supplies based on canonical supply demand models. However, this argument is unable to explain the slowdown in relative demand growth during the early 1990s.

There is no unique explanation for the complex pattern of changes in the U.S. wage distribution function during the 1990s. Having argued that labor market institutional factors, skill biased technological change, relative demand for skilled labor, effects of international trade and their dynamic interactions play very important roles in explaining changes to the wage distribution function; this paper provides an explanation of these asymmetric changes in the U.S. wage distribution function by considering the role of human capital variables in the canonical Mincer earnings framework and finds that changes in the composition of the labor force play a secondary role, whereas the primary source of the asymmetric changes in the U.S. wage distribution during the 1990s is the changing labor market prices. This paper also shows that the steep increase of the upper-tail wage inequality in the U.S. labor market during the 1990s is not caused primarily by the heterogeneous returns from education.

Appendix

Proof of property 1: Complete Mappings

By assumption, $F_{w_t|x_t}(\cdot)$ is monotonically increasing over the domain of x_t so the inverse $F^{-1}_{w_t|x_t}(\tau)$ exists and is well defined. Since $\tau \in (0,1)$, by applying the probability integral transformation theorem we set

$$\begin{aligned} &\tau = F_{w_t|x_t}(w_t) \\ &\Rightarrow F^{-1}_{w_t|x_t}(\tau) = w_t. \end{aligned}$$

So for each value of $\tau \in (0,1)$ we get a unique draw from $F_{w_t|x_t}(\cdot)$. We know that the number of values τ can take in $(0,1)$ is countable infinite. Again, by assumption, $\mathcal{W}_t$ is closed and bounded in $\mathbb{R}^k$ so for each value of $w_t \in \mathcal{W}_t$, we can find a unique $\tau \in (0,1)$. This implies that as the number of draws (m) goes to infinity we can recover every possible values from $F_{w_t|x_t}(w_t)$.

Proof of property 2: Convergence in Distribution

Under some regularity conditions, Powell (1991) shows in Theorem 2, the joint distribution of $\theta^t = \begin{pmatrix} \lambda_\tau^t \\ \beta_\tau^t \end{pmatrix}$ for $t = 0$ and 1 is,

$$\sqrt{n}\left(\hat{\theta}^t(\tau) - \theta_0(\tau)\right) \xrightarrow{d} \mathcal{N}\left(0, H_n^t(\theta)^{-1} V_n^t(\theta) H_n^t(\theta)^{-1}\right). \tag{2.11}$$

The Hessian matrix H_n is

$$H_n^t(\theta^t) = \frac{1}{n}\sum_{i=1}^{n} E\left[f_w(g(x_i^t, \theta^t)|x_i^t)\dot{g}_i^t(\theta_0^t)(\dot{g}_i^t(\theta_0^t))'\right] \tag{2.12}$$

where $f_w(g(\cdot)|x_i^t)$ is the conditional density of w_i given x_i, $\dot{g}_i = \delta g(x_i^t, \theta^t)/\delta\theta^t$ and

$$V_n^t(\theta^t) = \frac{1}{n}\sum_{i=1}^{n} \psi_i(\theta^t)[\psi_i(\theta^t)]' \tag{2.13}$$

where $\psi_i(\theta^t) = [\tau - \mathbb{I}(w_i < g(x_i^t, \theta^c))]\, t_i(\theta^t)$ and

$$t_i(\theta^t) = min\left[\frac{\delta^- s_i[h(x_i^t, \theta^t)]}{\delta h}, \frac{\delta^+ s_i[h(x_i^t, \theta^t)]}{\delta h}\right]. \tag{2.14}$$

The counterfactual conditional quantile function obtained from the simulation method described in the Section 2 has the form

$$\begin{aligned} w_i^c &= q(f(x_i, \theta^c) + u_i^c) \\ &= g^c(x_i, \theta^c, u_i^c) \end{aligned}$$

where u_i^c is the error term. Note that the superscript c denotes the counterfactual. The above function can be rewritten in the form of a nonlinear regression model with additive error,

$$w_i^c = g(x_i, \theta^c) + v_i^c \quad where \;\; v_i^c = g(x_i, \theta^c, u_i^c) - g(x_i, \theta^c)$$

Assumptions:

A1. The transformation $g^c(x_i, \theta^c, u_i)$ is of the form

$$g^c(x_i, \theta^c, u_i^c) = s^c[h^c(x_i, \theta^c, u_i^c), x_i] \equiv s_i^c[h^c(x_i, \theta^c, u_i^c)] \tag{2.15}$$

where $h(x_i^t, \theta, u_i)$ is scalar valued and continuously differentiable with respect to θ and $s_i(.)$ is (right and left) differentiable and satisfies the other regularity conditions described by Powell (1991).

A2. The parameter vector $\theta_0^c = ((\lambda_0^c)', (\beta_0^c)')'$ is an interior point of the parameter space Θ

By assumption $\hat{\theta}^c$ is the quantile estimator that minimizes $g^c(.)$ and, also by using the above two assumptions, we obtain the following F.O.C.

$$\Psi_n^c(\hat{\theta}^c) = \frac{1}{n}\sum_{i=1}^{n} \left[\tau - \mathbb{I}(w_i < g(x_i^t, \theta^c))\right] t_i(\theta^c) = 0 \tag{2.16}$$

where

$$t_i(\theta^c) = min \left\{ \frac{\delta^- s_i[h(x_i^t, \theta^t)]}{\delta h}, \frac{\delta^+ s_i[h(x_i^t, \theta^t)]}{\delta h} \right\} \frac{\delta h(x_i, \theta)}{\delta \theta}.$$

Denoting $\psi_i(\theta^c) = [\tau - \mathbb{I}(w_i < g(x_i^t, \theta^c))]\, t_i(\theta^c)$ we have,

$$\Psi_n^c(\hat{\theta}^c) = \frac{1}{n}\sum_{i=1}^{n} \psi_i^c(\hat{\theta}^c) = o_p(\frac{1}{\sqrt{n}}). \tag{2.17}$$

Now the relation in equation (17) has been established, the conditions of Theorem 2 of Powell (1991) have been satisfied. By applying Powell's result shown above, we obtain the asymptotic normality of the estimator $\hat{\theta}^c$

$$\sqrt{n}\left(\hat{\theta}^c(\tau) - \theta_0^c(\tau)\right) \xrightarrow{d} \mathcal{N}\left(0, H_n^c(\theta)^{-1} V_n^c(\theta) H_n^c(\theta)^{-1}\right) \tag{2.18}$$

where $H_n^c(\theta^c) = \frac{1}{n}\sum_{i=1}^{n} E\left[f_w(g(x_i^c,\theta^c)|x_i^c)\dot{g}_i^c(\theta_0^c)(\dot{g}_i^c(\theta_0^c))'\right]$, $V_n^c(\theta^c) = \frac{1}{n}\sum_{i=1}^{n}\psi_i(\theta^c)[\psi_i(\theta^c)]'$, and $f_w(g^c(\cdot)|x_i^t)$ is the conditional density of w_i^c given x_i, $\dot{g}_i^c = \delta g^c(x_i^t,\theta^c)/\delta\theta^c$.

The next step is to show that Y_n is a continuous function of $\theta^c \in \Theta$ where Θ is the parameter space of θ^c. We can write Y_n as a composite function of h_1 and h_2 in the following way:

$$\begin{aligned} Y &= g^c(x'_{t=0}\beta_\tau^{t=1}, \lambda_\tau^{t=0}) \\ &= \left(\lambda_\tau^{t=0} x'_{t=0}\beta_\tau^{t=1} + 1\right)^{1/\lambda_\tau^{t=0}} \\ &= h_1(h_2(\cdot)) \end{aligned}$$

where $h_1 = 1/\lambda_\tau^{t=0}$ and $h_2 = \lambda_\tau^{t=0} x'_{t=0}\beta_\tau^{t=1} + 1$. We note that h_1 and h_2 both are continuous function in the parameter space Θ. By applying the theorem (Walter Rudin, Theorem 4.10, page 87) which states a continuous function of a continuous function yields a continuous function, we conclude that Y_n is continuous in θ^c. Now by applying the Continuous mapping theorem we obtain the following result,

$$F_n(\hat{Y}_n) \xrightarrow{d} F(Y) \quad as \;\; n \to \infty$$

Graphs and Tables

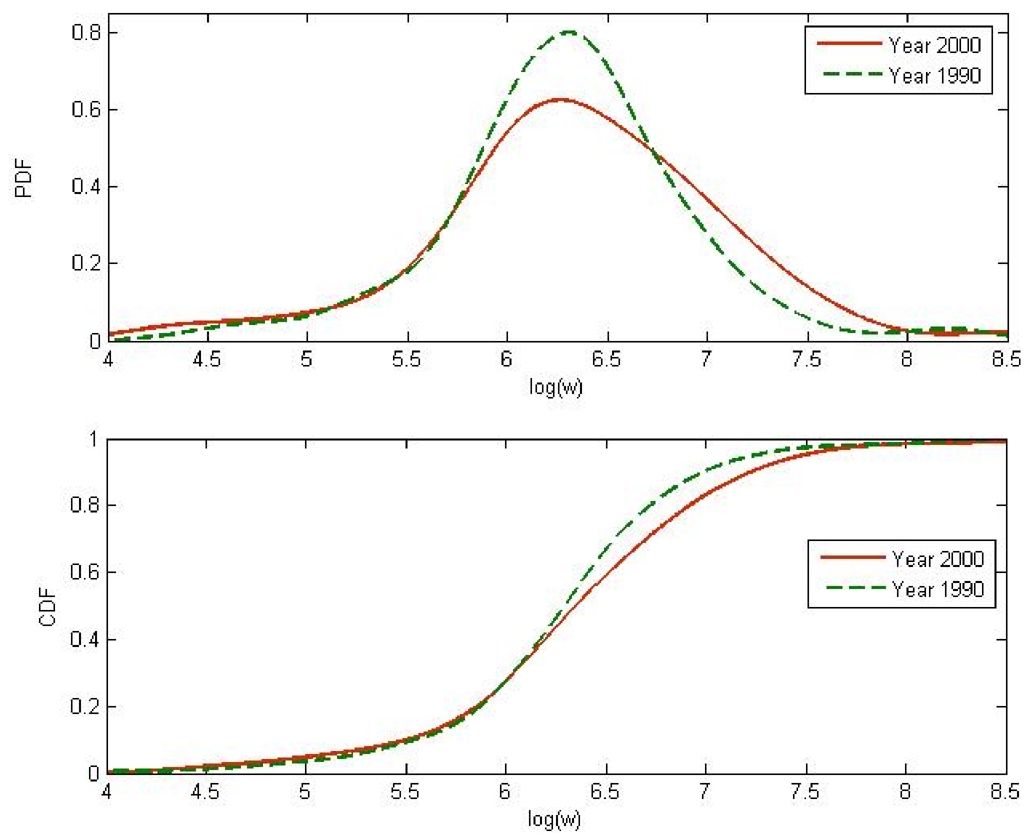

Figure 2.1: Male Weekly Log Wage Density and Distribution Function for the Years 1990 and 2000

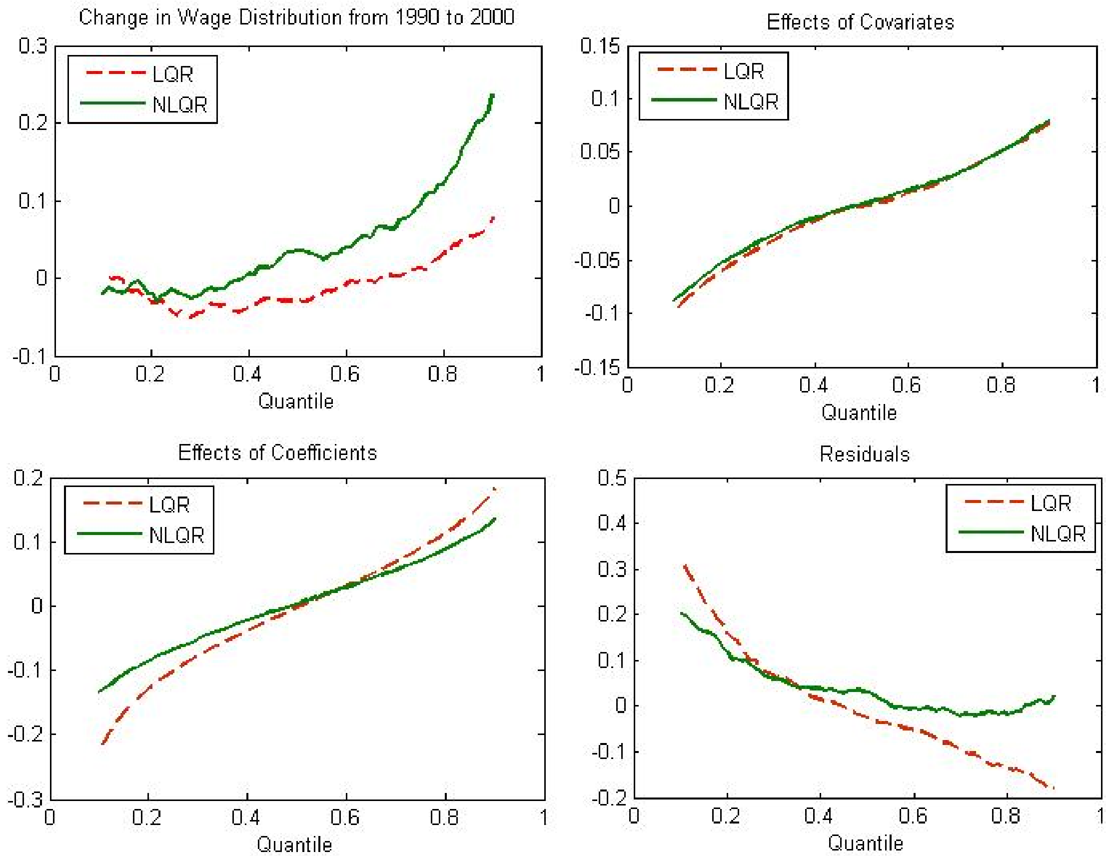

Figure 2.2: Decomposition Results by Linear and Non-linear Quantile Regression Methods

Table 2.1: Descriptive Statistics (Percentage and Average Wage) for the Period 1990-2000 by Education, Experience and Race

	Percentage			Mean Wage		
	2000	1990	Changes	2010	2000	Changes
Education						
HS Dropout	6.243	9.253	-3.010	6.055	6.025	0.030
HS Grad	24.820	23.643	1.177	6.265	6.272	-0.007
Some College	34.420	32.403	2.017	6.464	6.437	0.026
College Grad	20.177	18.623	1.553	6.860	6.715	0.090
Post College Grad	14.340	16.077	-1.737	7.011	6.869	0.141
Experience						
Exp 0-10 yrs	14.290	19.350	-5.060	6.919	6.737	0.181
Exp 11-20 yrs	82.537	75.243	7.293	6.484	6.439	0.045
Exp 20-35 yrs	3.173	5.407	-2.233	6.179	6.157	0.022
Race						
White	92.177	92.123	0.053	6.562	6.509	0.053
Black	7.823	7.877	-0.053	6.234	6.161	0.073

Table 2.2: Conditional Distribution Model Specification Test for Year 2000

	GCCM-QR		GCCM-BCQR	
No of Replications	10%	5%	10%	5%
$n = 50$	0.303	0.157	0.080	0.067
$n = 100$	0.214	0.147	0.067	0.037
$n = 200$	0.113	0.085	0.045	0.017

⋆ By Using the Generalized Conditional Cramer-von Mises (GCCM) test proposed by Rothe and Wied (2013), we test two functional forms of the conditional quanile function for the 5 and 10 percent critical values. The numbers in the table represent the rejection probabilities from n replications of the simulation process proposed by Rothe and Wied (2013).

Table 2.3: Estimated Changes in the U.S. Male Unconditional Wage Distribution over the Period 1990-2000 by Using the Quantile Regression and Box-Cox Quantile Regression

	Linear QR			Box-Cox QR		
Index	2000	1990	Changes	2000	1990	Changes
10th quant	5.663	5.669	−0.005	5.859	5.873	−0.014
	(5.660, 5.665)	(5.666, 5.671)		(5.857, 5.861)	(5.872, 5.875)	
25th quant	6.074	6.116	−0.042	6.164	6.183	−0.018
	(6.072, 6.076)	(6.114, 6.118)		(6.163, 6.165)	(6.181, 6.184)	
50th quant	6.467	6.495	−0.027	6.574	6.539	0.034
	(6.465, 6.468)	(6.493, 6.496)		(6.573, 6.575)	(6.538, 6.540)	
75th quant	6.843	6.830	0.013	6.940	6.844	0.095
	(6.842, 6.845)	(6.828, 6.831)		(6.938, 6.942)	(6.843, 6.845)	
90th quant	7.291	7.213	0.077	7.378	7.146	0.232
	(7.288, 7.294)	(7.210, 7.215)		(7.376, 7.381)	(7.144, 7.148)	
Skewness	−1.883	−1.099	−0.783	0.575	0.231	0.344
	(−1.904, −1.862)	(−1.135, −1.064)		(0.570, 0.581)	(0.226, 0.236)	
Scale	0.115	0.107	0.008	0.115	0.103	0.012
	(0.115, 0.116)	(0.106, 0.107)		(0.115, 0.116)	(0.102, 0.104)	
Gini Coeff	0.081	0.066	0.015	0.052	0.045	0.006
	(0.081, 0.082)	(0.066, 0.067)		(0.052, 0.053)	(0.045, 0.046)	

* The numbers in the table represent the estimated weekly log wages, therefore their differences indicate the percentage changes in wages. The numbers in the parenthesis show the 95 percent bootstrap confidence interval which has been generated by 1000 replications. To construct the unconditional wage distribution functions, I have used 3000 quantiles between 0 and 1 from uniform distribution.

Table 2.4: Decomposition of Wage Distribution Function for the Period 1990-2000 by Using the Quantile Regression and Box-Cox Quantile Regression

	Linear QR			Box-Cox QR		
Index	Composition	Wage Structure	Residual	Composition	Wage Structure	Residual
10th quant	-0.099	-0.224	0.341	-0.088	-0.135	0.208
	$(-0.100, -0.098)$	$(-0.224, -0.225)$		$(-0.088, -0.089)$	$(-0.135, -0.134)$	
25th quant	-0.047	-0.100	0.141	-0.041	-0.067	0.090
	$(-0.047, -0.048)$	$(-0.101, -0.100)$		$(-0.041, -0.040)$	$(-0.067, -0.066)$	
50th quant	-0.000	-0.002	0.001	0.001	0.003	0.0294
	$(-0.001, -0.000)$	$(-0.002, -0.001)$		$(0.001, 0.002)$	$(0.003, 0.004)$	
75th quant	0.040	0.089	0.128	0.039	0.070	-0.016
	$(0.040, 0.041)$	$(0.089, 0.090)$		$(0.039, 0.040)$	$(0.070, 0.071)$	
90th quant	0.076	0.181	-0.247	0.079	0.134	0.016
	$(0.076, 0.077)$	$(0.181, 0.182)$		$(0.079, 0.080)$	$(0.134, 0.135)$	
Skewness	0.129	-0.129	0.259	0.105	0.033	0.072
	$(0.125, 0.133)$	$(-0.134, -0.125)$		$(0.101, 0.110)$	$(0.028, 0.038)$	
Scale	-1.886	-0.575	-1.311	0.486	0.253	0.232
	$(-1.893, -1.878)$	$(-0.576, -0.573)$		$(0.485, 0.487)$	$(0.253, 0.254)$	
Gini Coeff	0.388	0.247	0.140	0.267	0.123	0.143
	$(0.387, 0.389)$	$(0.247, 0.248)$		$(0.266, 0.268)$	$(0.123, 0.124)$	

* Composition effect measures the impact due to the changes in labor force composition and the wage structure effect measures the market returns of the workers' characteristics. The unexplained part is called the residual effect.

Table 2.5: Impacts of Human Capital Variables to Changes in the Male Wage Distribution Function over the Period 1990-2000

Index	Education	Experience	Race	Residual
10th quant	-0.048	-0.073	-0.027	-0.134
	$(-0.049, -0.047)$	$(-0.073, -0.072)$	$(-0.028, -0.027)$	
25th quant	-0.030	-0.047	-0.022	-0.081
	$(-0.030, -0.029)$	$(-0.048, -0.047)$	$(-0.022, -0.021)$	
50th quant	-0.000	-0.007	-0.010	0.016
	$(-0.001, 0.000)$	$(-0.008, -0.007)$	$(-0.011, -0.010)$	
75th quant	0.019	0.017	-0.009	0.067
	$(0.019, 0.020)$	$(0.017, 0.018)$	$(-0.010, -0.009)$	
90th quant	0.042	0.054	0.002	0.133
	$(0.041, 0.043)$	$(0.054, 0.055)$	$(0.002, 0.003)$	

* Impacts of human capital variables are estimated by: $F(w_{t=1}) - F\left(w_{t=1}; x'_{t=1}, x_{t=0}\right)$ for $\tilde{x}_t$ where x'_t represents the set of all the other variables except $\tilde{x}_t$.

Table 2.6: Regression and Quantile Regression Models for the College High School Log Wage Gap, 1963-2005

	(1)				(2)			
	OLS	10th Q	50th Q	90th Q	OLS	10th Q	50th Q	90th Q
CLG/HS relative supply	−0.609	−0.931	−0.590	0.549	−0.728	−0.459	−0.689	−0.707
	(0.102)	(0.068)	(0.107)	(0.010)	(0.155)	(0.061)	(0.206)	(0.062)
Log real minimum wage					−0.049	−0.150	−0.011	−0.017
					(0.051)	(0.010)	(0.060)	(0.016)
Male prime-age unemp rate					0.004	−0.007	0.003	0.004
					(0.004)	(0.001)	(0.005)	(0.002)
Time	0.021	0.033	0.023	0.016	0.028	0.015	0.0282	0.022
	(0.006)	(0.002)	(0.006)	(0.006)	(0.007)	(0.002)	(0.010)	(0.003)
$\text{Time}^2/100$	0.030	0.0267	0.018	0.043	0.017	0.023	0.010	0.038
	(0.015)	(0.010)	(0.016)	(0.015)	(0.017)	(0.006)	(0.021)	(0.008)
$\text{Time}^3/1000$	−0.006	−0.007	−0.005	−0.008	−0.005	−0.004	−0.004	−0.007
	(0.002)	(−0.433)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
Observations	43	43	43	43	43	43	43	43
R-squared/Pseudo R-squared	0.952	0.702	0.813	0.838	0.955	0.734	0.814	0.850

	(3)				(4)			
	OLS	10th Q	50th Q	90th Q	OLS	10th Q	50th Q	90th Q
CLG/HS relative supply	−0.403	−0.319	−0.399	−0.600				
	(0.067)	(0.015)	(0.105)	(0.045)				
Log real minimum wage	−0.117	−0.234	−0.065	−0.089	−0.144	−0.173	−0.004	0.121
	(0.047)	(0.018)	(0.070)	(0.035)	(0.065)	(0.064)	(0.097)	(0.028)
Male prime-age unemp rate	−0.001	−0.006	−0.001	0.004	−0.018	−0.010	−0.018	−0.008
	(0.004)	(0.001)	(0.005)	(0.002)	(0.003)	(0.001)	(0.004)	(0.001)
Time	0.017	0.014	0.017	0.023	0.006	0.008	−0.006	0.006
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)
Observations	43	43	43	43	43	43	43	43
R-squared/Pseudo R-squared	0.944	0.725	0.788	0.838	0.891	0.543	0.712	0.745

Table 2.7: Regression and Quantile Regression Models for the College High School Log Wage Gap by Potential Experience Group 1963-2005, Males and Females Pooled

	All Experience Groups							
	OLS	10th Q	50th Q	90th Q	OLS	10th Q	50th Q	90th Q
Own supply minus agg supply	−0.282	−0.238	−0.296	−0.284	−0.281	−0.212	−0.321	−0.341
	(0.027)	(0.054)	(0.046)	(0.036)	(0.026)	(0.038)	(0.039)	(0.050)
Aggregate supply	−0.600	−0.738	−0.561	−0.507	−0.705	−1.012	−0.732	−0.521
	(0.087)	(0.149)	(0.150)	(0.144)	(0.130)	(0.193)	(0.190)	0.209
Log real minimum wage					−0.074	−0.126	−0.071	−0.119
					(0.037)	(0.067)	(0.055)	(0.058)
Male prime-age unemp rate					0.004	0.009	0.004	−0.001
					(0.003)	(0.004)	(0.005)	(0.006)
Time	0.027	0.034	0.024	0.023	0.031	0.044	0.030	0.023
	(0.004)	(0.008)	(0.007)	(0.006)	(0.006)	(0.009)	(0.009)	(0.009)
$\text{Time}^2/1000$	−0.009	−0.017	−0.005	−0.005	−0.012	−0.026	−0.010	−0.007
	(0.005)	(−0.433)	(0.008)	(0.007)	(0.006)	(0.010)	(0.008)	(0.008)
Observations	172	172	172	172	172	172	172	172
R-squared/Pseudo R-squared	0.863	0.576	0.641	0.682	0.868	0.594	0.647	0.687

Potential Experience Groups	0-9 yrs		10-19 yrs		20-29 yrs		30-39 yrs	
	OLS	Median	OLS	Median	OLS	Median	OLS	Median
Own supply minus agg supply	−0.169	−0.173	−0.325	−0.344	0.101	0.052	0.002	0.038
	(0.130)	(0.101)	(0.084)	(0.201)	(0.084)	(0.176)	(0.119)	(0.168)
Aggregate supply	−0.854	−0.955	−0.474	−0.349	−0.398	−0.382	−0.544	−0.596
	(0.262)	(0.207)	(0.182)	(0.429)	(0.224)	(0.448)	(0.190)	0.292
Log real minimum wage	−0.340	−0.355	−0.145	−0.130	0.098	0.125	0.028	0.043
	(0.076)	(0.062)	(0.049)	(0.119)	(.054)	(0.111)	(0.067)	(0.087)
Male prime-age unemp rate	0.005	0.011	0.002	−0.001	0.003	0.004	0.000	0.006
	(0.007)	(0.005)	(0.004)	(0.010)	(0.005)	(0.009)	(0.006)	(0.008)
Time	0.040	0.040	0.015	0.010	0.016	0.013	0.028	0.026
	(0.012)	(0.009)	(0.009)	(0.020)	(0.011)	(0.021)	(0.011)	(0.013)
$\text{Time}^2/1000$	−0.025	−0.021	0.010	0.012	0.000	−0.026	−0.021	−0.016
	(0.012)	(−0.008)	(0.009)	(0.020)	(0.010)	(0.020)	(0.012)	(0.015)
Observations	43	43	43	43	43	43	43	43
R-squared/Pseudo R-squared	0.926	0.787	0.969	0.839	0.868	0.666	0.647	0.687

Table 2.8: 100 × Observed and Composition Constant Changes in Overall and Residual Wage Inequality Measures by Using Counterfactual Decomposition Method

		Residual Inequality			Overall Inequality		
				Δ 90/50			
		1973-1989	1989-2005	1973-2005	1973-1989	1989-2005	1973-2005
Males	Observed	5.40	4.23	9.63	10.31	15.40	25.71
	1973 X's	0.64	2.16	2.81	9.51	8.96	18.47
	1989 X's	1.00	2.50	3.49	10.92	10.78	21.71
	2005 X's	1.69	2.22	3.90	9.30	9.19	18.49
Females	Observed	7.60	4.11	11.71	11.06	12.97	24.03
	1973 X's	3.60	0.88	4.48	10.82	7.92	18.74
	1989 X's	3.55	2.61	6.16	11.28	10.07	21.35
	2005 X's	4.38	4.04	8.42	10.90	10.62	21.53
				Δ 50/10			
		1973-1989	1989-2005	1973-2005	1973-1989	1989-2005	1973-2005
Males	Observed	7.39	−1.67	5.71	7.59	−2.43	5.61
	1973 X's	2.43	−0.37	2.06	10.77	3.93	14.70
	1989 X's	2.72	−0.05	2.67	10.84	3.27	14.11
	2005 X's	3.17	0.50	3.66	11.83	4.30	16.13
Females	Observed	8.84	0.02	8.86	13.28	0.39	13.66
	1973 X's	2.15	−1.80	0.35	10.55	5.10	15.65
	1989 X's	2.86	−1.44	1.43	9.81	5.60	15.41
	2005 X's	2.85	−0.22	2.64	9.77	7.11	16.88
				Δ 90/10			
		1973-1989	1989-2005	1973-2005	1973-1989	1989-2005	1973-2005
Males	Observed	12.79	2.56	15.34	17.90	12.97	30.87
	1973 X's	3.08	1.79	4.87	20.28	12.89	33.17
	1989 X's	3.72	2.45	6.16	21.76	14.05	35.81
	2005 X's	4.85	2.71	7.57	21.13	13.49	34.62
Females	Observed	16.43	4.14	20.57	24.23	13.35	37.69
	1973 X's	5.75	−0.91	4.84	21.37	13.02	34.38
	1989 X's	6.41	1.18	7.59	21.08	15.57	36.75
	2005 X's	7.23	3.82	11.05	20.67	17.74	38.41

CHAPTER III

The Role of Unionization on the U.S. Wage Inequality During the Period 1990-2010

3.1 Introduction

Over the last three decades a large number of studies have concentrated on explaining the widening of wage inequality in the U.S. labor market since the 1980s (see survey by Katz and Autor 1999). However, in recent years, many studies have found that most of the action has been at the very top tail of the wage distribution. Stories based on the returns from the human capital variables and the excess demand of skilled labor are not enough to explain the increase in wages at the upper tail of the U.S. wage distribution. Different approaches are needed to explain the rising gap between the upper and lower tails of the U.S. wage distribution, especially during the period 1990-2010.

Figure 1[1] depicts the U.S. top 10 percent income share since the 1913. Note that the top 10 percent income share curve for U.S. is U-shaped. In most recent years, the top 10 percent income shares are around 46 percent. In the past 100 years, this phenomenon has been only seen right before the 'Great Depression' in the early 1930s. Alvaredo et al. (2013) show that the shape of the income share curves of the top 1 percent in continental Europe and Japan are much closer to an L-shape rather than a U-shape. This suggests that the U.S.

[1] Source: World Top Income Database. Income is defined as pre-tax market income; it excludes government transfers and nontaxable fringe benefits.

has experienced higher income inequality compared to the other developed nations since the last three decades.

In the early 1980s, the overall wage inequality increased throughout the wage distribution. The right panel of figure 2 shows the lower tail wage inequality (50/10 percentile wage gap) and upper tail wage inequality (90/50 percentile wage gap) by using the March CPS (Current Population Survey) data. As shown both the lower tail and upper tail wage inequality have increased during the 1980s. However, since the 1990s there are two different patterns of changes in the U.S. wage inequality. The combined male-female upper tail wage inequality has increased since the 1980s but the lower tail wage inequality has decreased since the 1990s. This complex pattern of changes in wages is known as the polarization of the U.S. economy.

The left hand panel of figure 2 shows that the 90/10 percentile wage gap has increased around 20 percent during the period 1980-2012. The 90/10 percentile wage gap has increased around 10 percent in the early 1980s, then keep falling over the subsequent 10 years. Since the mid nineties, it has a steady upward trend. Autor et al. (2008), Firpo, Fortin and Limieux (2011), Alvaredo (2013) among others, show that the driving force of this increase in the 90/10 percentile wage gap is the substantial change in real wages at the upper tail and a lack of increases in real wages at the lower tail of the U.S. wage distribution. However, a question still remains unsolved: why did the 50/10 percentile wage gap fall during the 1990s and then remain the same during the period 2005-2010? The motivation of this study is to find out the role of the union to explain this phenomenon. Unions play a very important role at both the top and bottom tails of the U.S. wage distribution because the U.S. labor market has gone through huge changes in terms of the union structure since the 1990s.

The behavior of the tails of the U.S. wage distribution is important for explaining the overall wage inequality because the top 10 percent are most responsible for the steep increase in the U.S. wage inequality since the 1980s. Alverado et al. (2013) show that apart from the bubble in 1920s, the U.S. top 1 percent income share is between 15 percent to 20 percent till the 1980s and the top 1 percent income share has risen around 135 percent over the period 1980-2007. There is a fall in the income share during the recession of 2008-2009, but it rebounded again in 2010. On the other extreme, at the lower tail, workers real income become stagnant or negative depending on the subgroup of the education levels during the same period of time.

Figure 3 shows that male and female workers experience slightly different patterns of changes in wage inequality, especially at the lower tail of the wage distribution over the last decades. For men, the lower tail wage gap is falling over time, whereas for women, the lower tail wage gap remains almost constant since the 1990s. The male-female wage gaps also fall substantially, especially at the upper tail of the wage distribution. Autor et al. (2008) show that the gender wage gaps at different parts of the wage distribution fall by education and occupations over the last two decades. These imply that the overall pattern of changes in wage distribution does not reflect the changes in female wage distribution function over the period 1990-2010.

Figure 4 shows that there is a sharp fall in male union members compared to females over the last two decades. The percentage of male union members has fallen from 23 percent to 15 percent whereas the percentage of female union workers has gone down from 15 percent to 13 percent. Figure 5 shows the composition of male and female union workers with five different education levels for the three discrete time periods of 1990, 2000 and 2010. In the left panel, we see that during the 1990s the coverage of female union workers is uniform in terms of the skill distribution. However, over the last two decades, the union coverage has concentrated near the top of the skill distribution. Thus, unions decrease the within sector wage inequality among female workers.

Right panel of figure 5 shows that union coverage tends to be concentrated at the middle of the skill distribution for males. High school drop outs and high school graduates represent two thirds of the total union members during the 1990s, whereas their share falls by less than half in 2010. These suggest that unionization rates vary across the wage distribution, and the union membership has fallen disproportionately for low skilled workers. Lewis (1986) shows that unions raise the wage more for low skilled workers. This implies that unions play a substantial role in equalizing wages across groups and a sharp fall in unionization at the lower part of the skill distribution increases the between group wage inequality for the male workers.

A number of previous studies, including Freeman (1980, 1993), Lemieux (1993), Card (1996, 2001), DiNardo, Fortin and Lemieux (1997), Machin (1997), Gosling and Lemieux (2001), Card, Lemieux and Riddell (2003), and Firpo, Forin and Lemieux (2009) have showed the role of unions in the U.S. wage inequality. Most of these studies have focused on men over the period 1970-2000. One contribution of this study in the previous literature is to provide a comprehensive analysis of the contribution of unionization on wage inequality for both men and women over the last two decades.

This paper proposes a new econometric model, 'Box-Cox Unconditional Quantile Regression', to capture the effects of the union more accurately at the two tails of the wage distribution function. By using this new estimation method we find that unionization can explain around 20 to 25 percent of the total changes in the lower tail wage inequality and nothing for the 90/10 percentile wage gap for men over the last two decades. For women, the impact of unionization on wage inequality is much less than for men. Unionization can explain around 0.2 percent of total changes in the 90/10 percentile wage gap and has no effect on the lower tail wage inequality. DiNardo, Fortin and Lemieux (1996), Card (2001), Gosling and Lemieux (2001), and Card, Lemieux and Riddell (2003) all have also concluded that declining unionization has very little impact on female wage inequality in the U.S. labor market.

The paper is organized as follows. Section 2 reviews the existing wage decomposition methods. In section 3, I propose new econometric model to capture the effects of declining unionization at the two tails of the U.S. wage distribution. Section 4 represents the construction of the proposed decomposition method and its theoretical results. In section 5, I discuss the data and show the empirical results and conclude in section 6. All the derivations are shown in the appendix section.

3.2 Review of Decomposition Methods

Most of the previous studies used the linear regression framework to estimate the wage gaps between different parts of the income distribution. The regression model is not the right framework because if we fix any covariate at its median and plot the distribution of the dependent variable wage (w) at that given value of the independent variable, we see that the distribution of w is highly skewed for the U.S. labor market data over the period 1990-2010. This implies that quantile regression is the ideal model to capture the effects of the covariates at different parts of the wage distribution. The linear regression model can not capture the effects of the covariates on wage at the different parts of the distribution. The main advantage of the Oaxaca decomposition method is that it can separate out the price effect of workers' characteristics and the composition effect which is defined as the effect on wage due to changes in the distribution of the workers' characteristics compared to the base period. We can also decompose the composition effect by individual covariates (see Rothe 2013).

Over the last fifteen years there have been several papers that have studied decomposition methods, including Rothe (2012a, 2012b, 2010), Chernozhukov et al. (2012), Firpo et al. (2011, 2007), Antonczky et al. (2010), Altonji et al. (2008), Melly (2005), Machado and Mata (2005), Donald et al. (2000), Gosling et al. (2000) and Di-Nardo et al. (1996). (See also the extensive survey by Fortin, Lemieux, and Fipro (2011) on the wage decomposition literature.) These papers show how to construct a counterfactual distribution function by a wide range of parametric, semi-parametric or non-parametric methods. Many of these studies use the simulation method to construct the counterfactual distribution function and that is why those methods are computationally intensive and become practically infeasible for very large data sets.

Firpo et al. (2007, 2011) use a new estimation technique known as unconditional quantile regression to estimate the effect of X on the unconditional τth quantile of Y. Firpo, Fortin and Lemieux (2009) denote this estimated parameter as the partial or marginal effect of shifting the distribution of a covariate on the unconditional quantile. The unconditional quantile regression approach has attracted a lot of attention in the econometrics literature since Firpo, Fortin and Lemieux (2009) introduced the concept.

One important factor behind this interest is that conditional quantiles do not average up to their unconditional population counterparts. As a result, the estimates obtained by running a quantile regression can not be used to estimate the impact of X on the corresponding unconditional quantile. This implies that the quantile regression method cannot find out the impact of marginal increases in all the workers' education on some features of the distribution of wage, such as its moments, quantiles, gini coefficient or other measures of income inequality.

In the Mincer wage equation the dependent variable wage (w) depends on the observable X and unobservable ϵ, in the form,

$$w = h(X, \epsilon) \tag{3.1}$$

where h is differentiable and strictly monotonic. Firpo, Fortin and Lemieux (2007, 2011) assume the linear additive separable model $w = X'\beta + \epsilon$. The linear form of the model implies that a small change t in covariate X_j simply shifts the location of the distribution of w by $\beta_j.t$ and leaves all other features of the distribution unchanged.

There is a fundamental problem with applying this method to U.S. wage distribution data. The model is based on the implicit assumption that conditional expectation of Re-centered Influence Function (RIF) is linear in parameters. Barsky et al. (2002) point out that when the true conditional expectation function is not linear, the decomposition based on a linear regression is biased. In particular, this assumption does not hold for a highly skewed U.S. wage distribution data.

Firpo, Fortin and Lemieux (2011) suggest using a re-weighting procedure to solve this problem as described in Di-Nardo et al. (1996). However, the re-weighting procedure becomes practically infeasible when there are too many continuous variables. Moreover, re-weighting can have some undesirable properties in small samples when there is a problem of common support. Frolich (2004) finds that re-weighting estimators perform poorly in this context. Autor et al. (2008) mention that the validity of the re-weighting counterfactual analysis depends on the partial equilibrium assumption that price and quantities are independent in the labor market. This assumption is economically invalid.

3.3 Econometric Model

In this paper, I provide an alternative solution to this problem by using a flexible Box-Cox transformation to equation (1), we can rewrite the equation (1) as

$$w^{\star} = \tilde{h}(X'\beta_{\tau}, \lambda_{\tau}, \epsilon) \tag{3.2}$$

In equation(2), it is assumed that $\tilde{h}$ is strictly monotonically increasing in $X'\beta_{\tau}$ and also depends on the shape parameter λ_{τ}. Moreover, $w^{\star} > 0$, $x \in \mathbb{R}^k$ are observed, while the parameter $\beta_{\tau} \in \mathcal{B}$ and $\lambda_{\tau} \in \mathbb{R}$ are unknown and $\tau \in (0,1)$. $\tilde{h}$ is given by

$$w^{\star} = \begin{cases} (w^{\lambda_{\tau}} - 1)/\lambda_{\tau} & if \;\; \lambda_{\tau} \neq 0 \\ log(w) & if \;\; \lambda_{\tau} = 0, \end{cases} \tag{3.3}$$

assuming $\lambda \in [\underline{\lambda}, \bar{\lambda}]$ to be a finite closed interval. The advantage of using the Box-Cox transformation is that the shape parameter λ_τ adjusts with each quantile to capture the precise shape of the conditional expectation function of $w^\star$.

3.3.1 Model Set Up

The Mincer equation is the most widely used specification of the empirical earnings equation in the labor economics literature. This equation is typically specified in the linear functional form,

$$w = \alpha + \beta_1\, union + X'\beta + \epsilon \tag{3.4}$$

In this analysis, unionization is the key interest variable where union status is a binary variable representing whether a worker is a union member or not. X represents the set of control variables consisting of education, experience, race, gender and other sets of demographic dummy variables.

Buchnisky (1998) mentions that to calculate the potential female work experience, we need to take into account that females can leave the labor market a for short period of time due to home activities related to child birth. We follow Buchnisky's (1998) method to estimate the adjusted female work experience,

$$Y_p = \gamma_1 x_p + \gamma_2 x_p^2 + \delta_1 x_p \times chld + \delta_2 x_p^2 \times chld = \gamma_1 x_p \left(1 - \frac{\delta_1}{\gamma_1} chld\right) + \gamma_2 x_p^2 \left(1 - \frac{\delta_2}{\gamma_2} chld\right) \tag{3.5}$$

where x_p denotes potential experience[2] and chld is the number of children in the family. The dependent variable (Y_p) in this equation is a dummy variable that takes the value 1 if a woman works for pay, and zero, otherwise.

[2] potetial experience = Age - 6 - years of schooling

The other independent variables include: family composition by age, children by age groups, personal non-earned income, other family income (excluding personal income), education, number of children in the family, dummy variables for race, metropolitan area, and marital status. The term $\left(1 - \frac{\delta_1}{\gamma_1} chld\right)$ is the adjustment factor we need to consider to potential experience in order to obtain the actual experience, the variable of interest. The adjustment term x_p^2 be $\left(1 - \frac{\delta_2}{\gamma_2} chld\right)$ allows more flexible approximation of the dependent variable Y_p.

3.3.2 Model Identification

Firpo, Fortin and Lemieux (2009) defined 'Unconditional Partial Effects' as the small location shift in the distribution of a continuous variable X on the distributional statistic $\nu(F_Y)$,

$$UQPE(\nu) = \lim_{t \to 0} \frac{\nu(F^{\star}_{Y,t}) - \nu(F_Y)}{t} \tag{3.6}$$

where $\nu(F^{\star}_{Y,t}) = \int F_{Y|X}(y|x).dF_X(x-t)$ and $F_{Y|X}(\cdot)$ is continuous and smooth function. Firpo, Fortin and Lemieux (2009) show that any distributional statistic $\nu(F_y)$ can be expressed in terms of the conditional expectation of the Re-centered Influence Function $(RIF(y;\nu,F_Y))$ given X:

$$\nu(F_Y) = \int E[RIF(y;\nu,F_Y)|X=x].dF_X(x) \tag{3.7}$$

where $RIF(y;q_\tau) = q_\tau + \frac{\tau - \mathbb{I}\{y \leq q_\tau\}}{f_y(q_\tau)}$ and q_τ is the τth sample quantile. The above results show that when we are interested in the impact of covariates on a specific distributional statistic $\nu(F_Y)$ such as the quantile, we simply need to integrate over $E[RIF(y;\nu,F_Y)|X=x]$.

Proposition 1[3]: Assuming that the structural form $Y = h(X,\epsilon)$ is strictly monotonic in ϵ and X and ϵ are independent, then the parameter UQPE(τ) is:

[3] The proof of this proposition is available in the appendix

$$UQPE(\tau) = \beta_j^\tau (1 + \lambda_\tau q_\tau)^{(1-\lambda_\tau)/\lambda_\tau} \tag{3.8}$$

Note that for the linear model $\lambda_\tau = 1$ and the $UQPE(\tau)$ becomes β_j^τ as shown by Firpo, Fortin and Lemieux (2009).

The proposition 1 result is a generalization of Firpo et al.'s (2009) linear model because the linear model is a special case of Box-Cox model. This result can not be derived without the independence assumption between X and ϵ. In many practical cases this assumption may not be satisfied. To identify the model, we then use the control variable approach introduced by Imbens and Newey (2009). Ghosh (2013) shows a generalization of this result by using the control variable approach introduced by Imbens and Newey (2009) in the presence of endogenous regressors in the model.

Firpo et al. (2009) also show that the unconditional quantile regression function, $m_\tau(X) = E[RIF(\cdot)|X]$ can be used to consistently estimate the effects of X on the unconditional τth quantile of w. By using the above result we can consistently estimate the unconditional quantile regression function (m_τ) by the following result.

Proposition 2: Given that the conditional expectation function of $RIF(\cdot)$ exists and X and ϵ are independent, the Box-Cox unconditional quantile regression function is given by:

$$m_\tau = X'\beta_\tau (1 + \lambda_\tau q_\tau)^{(\lambda_\tau - 1)/\lambda_\tau}$$

Again, note that for the linear model, λ_τ equals to 1 and the m_τ becomes $X'\beta_j^\tau$ as shown by Firpo, Fortin and Lemieux (2009). The above result can be easily derived from proposition 1 as long as the independence assumption between X and ϵ holds. If the assumption does not hold, m_τ can be identified by using the control variable method as shown in Ghosh (2013). We define $\theta_\tau = (\beta_\tau \;\; \lambda_\tau)'$. The convergence of $\hat{\theta}_\tau$ is guaranteed since the objective function is convex. By following the similar approach as shown by Firpo et al. (2009), one can easily show that $\hat{\theta}_\tau$ converges to θ_τ asymptotically.

To estimate UQPE and m_τ, I need to estimate three parameters. The usual τth sample quantile which can be represented as in Koenker and Bassett (1978), as

$$\hat{q}_\tau = \underset{q_\tau}{argmin} \sum_{i=1}^{n} (\tau - \mathbb{I}\{w_i - q_\tau \leq 0\})(w_i - q_\tau)$$

and we estimate $\hat{\beta}_\tau$ and $\hat{\lambda}_\tau$ by using nonlinear least square, which is given by

$$\hat{\theta}_\tau = argmin \begin{cases} \sum\limits_{i=1}^{n} \left((1 + \lambda_\tau RIF_i)^{1/\lambda_\tau} - x_i'\beta_\tau\right)^2 & for \ \ \lambda_\tau \neq 0 \\ \sum\limits_{i=1}^{n} \left(exp\{RIF_i\} - x_i'\beta_\tau\right)^2 & for \ \ \lambda_\tau = 0, \end{cases} \tag{3.9}$$

where $\theta_\tau = (\beta_\tau \ \ \lambda_\tau)'$.

3.3.3 Markup Factor

We define the markup factor as $MF_\tau = (1 + \lambda_\tau q_\tau)^{(\lambda_\tau - 1)/\lambda_\tau}$ since in both the propositions, this is the additional term we multiply compared to the linear RIF regression[4] model results derived by Firpo, Fortin and Lemieux (2009). This markup factor varies over each quantile through the values of λ_τ and q_τ. The advantage of the Box-Cox model is that when the conditional expectation function is non-linear, the shape parameter (λ_τ) in the Box-Cox model adjusts with each quantile through the non-linear least square optimization.

Figure 6 shows the three dimensional plot of the markup factor where the first two axes are λ_τ and q_τ. The ranges of the axes are taken from the empirical analysis since we are interested on the behavior of the markup factor in our data. The ranges of the markup factor varies on different sets of values of q_τ and λ_τ. Figure 6 shows that the markup factor

[4]Re-centered influence function for quantile is defined as $RIF(w, q_\tau) = q_\tau + (\tau - I\{w \leq q_\tau\})/f_w(q_\tau)$

surface is monotonically increasing in λ_τ for any given value of q_τ. When λ_τ equals to 1, the markup factor also becomes 1 for all values of q_τ and we get a straight line in the upward sloping surface. This implies that we have two different regions in the markup factor surface which is divided by the straight line, one for λ_τ less than 1 and one where λ_τ is greater than 1.

The markup factor is less than 1 when λ_τ is less than 1 for all values of q_τ. If we use the linear RIF regression model when λ_τ is less than 1 then we overestimate UQPE and m_τ because we multiply β_τ by a bigger number than the true value which is less than 1. Similarly when λ_τ is greater than 1, we underestimate UQPE and m_τ. By comparing with the Box-Cox model, we see that at the upper tail of the wage distribution function, the linear unconditional quantile regression model underestimates the unconditional partial effects and RIF regression functions around 5 to 8 percent whereas at the lower tail, it overestimates around 2 to 4 percent for these specific set of values of q_τ and λ_τ.

3.3.4 Decomposition of Changes in Wage Distribution

In this subsection, we show how to formally decompose the changes of the wage distribution function into composition effect and wage structure effect by using the non-linear RIF regression approach as shown above. As is well known, the standard regression analysis can be used to perform a Oxaca-Blinder decomposition for the mean of a distribution. RIF regression allow us to perform the same kind of decomposition for any distributional statistics for the distribution function.

Let's consider two time periods, $t = 0$ and $t = 1$. In general, any distributional parameter can be written as a functional $\nu(F_w)$. Denote $\Delta\nu$ be the overall change in the distributional statistics ν, then we have,

$$
\begin{aligned}
\Delta\nu &= \nu(F_{W_1|t=1}) - \nu(F_{W_0|t=0}) \\
&= \underbrace{\left[\nu(F_{W_1|t=1}) - \nu(F_{W_0|t=1})\right]}_{\text{Composition Effect}} + \underbrace{\left[\nu(F_{W_0|t=1}) - \nu(F_{W_0|t=0})\right]}_{\text{Wage Structure Effect}} + \ Residual \qquad (3.10)
\end{aligned}
$$

where the first bracketed terms represent the effect of changes in the distribution of covariates, which is denoted as the composition effect. The terms in the second bracket represent the effect of changes in the market returns of the covariates, which we denote as the wage structure effect. The rest is called the residual effect. We note that the key factor of this decomposition is to construct the counterfactual distributional statistics $\nu(F_{W_0|T=1})$. This term represents the distributional statistics of the counterfactual distribution function where the covariates are distributed as in period $t = 0$ but the workers are paid according to period $t = 1$.

We denote Δ_ν^{CE} and Δ_ν^{WE} as the composition effect and wage structure effect respectively. By applying Firpo et al.'s (2009) result, any distributional statistics can be expressed in terms of the expectation of the conditional Re-centered Influence Function. We can rewrite the composition and wage structure effect as,

$$
\begin{aligned}
\Delta_\nu^{CE} &= E[m_{t=1}^\nu] - E[m_c^\nu] \\
\Delta_\nu^{WE} &= E[m_c^\nu] - E[m_{t=0}^\nu]
\end{aligned}
$$

where, $\quad E[m_{t=1}^\nu] = X_t'\beta_\tau^t(1 + \lambda_\tau^t q_\tau)^{(1-\lambda_\tau^t)/\lambda_\tau^t}; \qquad t = 0, 1$

and $\quad E[m_c^\nu] = X_t'\beta_\tau^{t=0}(1 + \lambda_\tau^{t=1} q_\tau)^{(1-\lambda_\tau^t)/\lambda_\tau^t}$

To obtain the impact of any distributional statistics of a given individual covariate $(\tilde{x}_t)$, we need to construct distributional statistics of another counterfactual distribution function, such that the distribution of all the covariates remain same as in period 1 and only $(\tilde{x}_t)$ is distributed as in period 0. Then we get,

$$\nu(\tilde{x}_t) = \nu(F(w_{t=1})) - \nu(F\left(w_{t=1}; x'_{t=1}, x_{t=0}\right))$$

where $x_t = [\tilde{x}_t \;\; x'_t]$ and x'_t is the matrix consists of all the other covariates except $\tilde{x}_t$. The counterfactual distributional statistics $\nu(F\left(w_{t=1}; x'_{t=1}, x_{t=0}\right))$ can be obtained from $\nu(F(w_{t=1}; x_{t=0}))$ by using the method described above.

3.3.5 Construction of Distributional Statistics

To construct the distributional statistics, we follow the following steps:

1. Fix the set of specific values of the quantiles τ where $\tau \in (0, 1)$.

2. For each $\tau \in (0, 1)$, estimate $\hat{q}_\tau$ by using the linear quantile regression and estimate $f_w(\hat{q}_\tau)$ by using a kernel density estimator.

3. Estimate $\hat{\beta}_\tau$ and $\hat{\lambda}_\tau$ by using the non-linear least square.

4. Draw random samples from X for n times and estimate:

$$\{\hat{m}_t\}_{i=1}^{n} = X'\hat{\beta}_\tau(1 + \hat{\lambda}_\tau \hat{q}_\tau)^{(\hat{\lambda}_\tau - 1)/\hat{\lambda}_\tau}$$

5. Estimate the distributional statistics:

$$\hat{\nu}_t = E[\hat{m}_t]$$

There is a close connection between RIF regression and the distributional regression approach of Chernozhukov et al. (2012). In both cases, regression models are estimated for explaining the determinants of the proportion of workers earning less than a certain wage. Suppose that after estimating a model for proportions, we compute a counterfactual proportion based on the return to the covariate estimated with the Linear Probability Model as proposed by Firpo, Fortin and Lemieux (2009), then we obtain very similar results.

3.4 Data and Results

In this paper I have used Current Population Survey (CPS) data. CPS contains income and all the necessary demographic variables of individual workers. The data are drawn 5 percent self-weighted 1980-2010 samples, all from the Outgoing Rotation Group (ORG) Supplements of the Current Population Survey. The data consist of U.S.-born black and white men and women, aged 18-65, with positive annual earnings and hours worked in the year preceding the census and a nonzero sampling weight. The wage measure used is an hourly wage measure computed by dividing earnings by hours of work for workers not paid by the hour. For workers paid by the hour, we use a direct measure of the hourly wage rate. CPS weights are used throughout the empirical analysis. Annual income is expressed in 2010 dollars using the 'Personal Consumption Expenditures' price index.

In the data analysis, w is the real log hourly wage. The regressors consist of years of schooling, potential experience and experience square, union coverage, interaction terms of schooling and experience. I also include controls for marital status, race, and statistical metropolitan area in all the estimated models. Consistent with Autor et al. (2006) and Firpo et al. (2011), figure 7 shows that during the 1990s, changes in real wages at each quantile of the wage distribution follow a U-shaped curve. In the left panel we plot the same changes in wage during the period 2000-2010.

Figure 7 illustrates that wage changes in the top half of the distribution are quite similar for men and women during 1990-2010. Wages at the top have increased much compared to the middle part of the distribution function, resulting in top-end inequality. By contrast, inequality in the lower half of the distribution decreased rapidly during the 1990s since wages at the bottom grew substantially more than those in the middle of the distribution.

Table 1 represents the summary statistics of the male and female combined data. The CPS is a large nationally representative sample of the entire labor force. The income and worker's demographic variables in the samples represent the population of the U.S. labor force. The sample sizes are 69,651; 59,750 and, 84,239 for the years 1990, 2000 and 2010 respectively. Table 2 represents the summary statistics for men and women separately.

Table 3 shows unionization rates and percentage of union wage gaps between union and non-union workers across the five different education groups for men and women in 1990-2010. A key feature of the table is how union membership rates change over time across the five education groups. In 1990, high school dropouts and high school graduates represent two thirds of the total union members for men. This pattern of concentration of the union membership has changed in 2010 and become more evenly distributed across the skill distribution. Among women, unionization rates have concentrated more on the skilled workers in the 1990s and this pattern has become even stronger in the preceding twenty years.

Another interesting feature is the changes in the pattern of the union wage gaps across the five education groups. For men in 1990, the wage gaps ranged from 35 percent for the lowest skilled workers to 2 percent for the highest skilled workers. These estimates imply that unions have played an important role in reducing the wage inequality across the groups during the 1990s. These effects have increased substantially during the next two decades. The union wage gap for men of the lowest skill group is 57 percent and -17 percent for the most skilled workers in 2010. For women, the percentages of college graduate and post college graduate union workers have increased approximately 1 percent and 0.27 percent respectively, whereas the percentage of union wage gaps have decreased around 0.1 percent and 17 percent respectively, during the period 1990-2010.

3.4.1 Changes in the U.S. Wage Distribution Function

In Table 4 shows that the changes in the unconditional wage distribution for male and female workers by using the proposed Box-Cox RIF Regression model. The numbers in the parentheses represent the 95 percent bootstrap confidence interval which has been generated by 1000 replications. The first three columns show the real log hourly wage from the year 1990-2010 based on the 2010 consumer price index. The fifth and sixth columns represent the percentage change in real wage during the period 2000-2010 and 2000-1990. I also calculate the Gini coefficients and its changes over the period.

In the top and bottom panel of the fifth column in Table 4, we see that during the period 1990-2000, the estimated changes in real wages for men are around 0.06 to 3 percent while for women, the changes are around 5 to 10 percent. This is consistent with the findings that during the 1990s, gender gap reduces sharply. However, from the first three columns we see that the absolute wages for female workers are considerably lower compared to the male throughout the wage distribution. These suggest that gender inequality is still very high in the U.S. labor market.

During the period 2000-2010, changes in the real wages at the lower tail of the wage distribution for both men and women are similar but, at the median and 75th to 90th quantile, women have experienced slightly higher changes in real wages than men. However, the difference in changes of the female-male wage gap at the upper tail of the wage distribution is much smaller compared to the same difference in the 1990s.

By taking the difference of first and fifth columns of the first and fifth rows in the top and bottom panel of table 4, we see that over the last two decades the 90/10 percentile wage gap has increased for men around 10 percent and for women around 11 percent. Most of the changes have occurred during the 2000s. The changes of the Gini coefficients also suggest that wage inequality has increased more both for men and women during the 2000s compared to the 1990s. Figure 7 summarizes these changes by plotting the percentage changes in real wages for each quantile over the period 1990-2010.

3.4.2 Counterfactual Analysis

In Table 5, the wage distribution function has been decomposed into three parts, namely the composition effect, wage structure effect and residual effect. The residual effect is defined as the unexplained part of the change in the wage distribution as shown in Table 2. Row by row, I report the estimates of these three effects for different quantiles and various inequality measures. We note that for men at the lower tail of the wage distribution both composition effect and wage structure effect have almost no impacts on wage. As a result, we see there are not much changes in wages at the lower tail of the wage distribution. For women, changes in wages at the lower tail are positive because both composition effects and wage structure effects are greater than zero.

During both the periods, 1990-2000 and 2000-2010, and for both men and women at the upper tail of the wage distribution, the wage structure effect dominates the composition effect. These findings suggest that, at the upper tail of the wage distribution, the market returns of the high skilled workers' skills have increased significantly compared to the effects due to changes in the composition of the labor force during the period 1990-2010. During the 1980s, wage inequality in the U.S. labor market increased substantially, largely due to the changes in the education and experience composition of the labor force. However, during the period 1990-2010, the primary source of changes in the wage distribution is the wage structure effect. The composition effect plays a very minor role.

Figure 8 represents the decomposition results of the U.S. wage distribution function for men and women during the period 1990-2010. In the left side top and bottom panels, we show the composition effects for the sub-periods 1990-2000 and 2000-2010. We see that the composition curve is very flat and close to zero at the lower tail and around the median it goes to below zero for men. For women, the composition effects contribute around 0 to

2 percent of total changes in the wages throughout the wage distribution function for the period 1990-2000. In the top left panel, we see that the composition effects are around 0 to 1 percent whereas for women the effects are 1 to 2 percent during the period 1990-2010.

The right hand side panels of figure 8 show the wage structure effects for men and women. We note that during the 1990s, the wage structure effects of men around the median are less than zero which makes the total effects negative. Apart from the median, all other quantiles, effects are positive. This is still a puzzle for the labor economists: why is the skill prices of the median income earners lower compared to the workers at the lower tail of the wage distribution? During the period 2000-2010, the patterns of wage structure for men and women are very similar and increases sharply at the upper tail of the wage distribution. Wage structure effect is the dominating force of the total changes of the wage distribution function over the period 1990-2010.

This pattern of changes in the U.S. wage distribution in the 1990s differs sharply compared to the 1980s, with more rapid growth of real wages at the top of the wage distribution relative to the middle and the bottom of the wage distribution. Goos and Manning (2007) and Autor, Katz and Kearney (2005) characterize this pattern as the polarization of the U.S. labor market because the median income earners are pushed towards to the left tail of the U.S. wage distribution.

3.4.3 Effects of Unionization

Table 6 shows the unconditional partial effects of unionization at different quantiles for men and women over the period 1990-2010. A key feature of the table is the pattern of the Unconditional Quantile Partial Effect (UQPE) across the qunatiles for both men and women. For men in 1990, these ranged from 18.76 percent at the lower tail to 4.5 percent at the upper tail of the wage distribution. The UQPE coefficent 0.1876 implies that one percentage point increase of the proportion of union members at the 10th quantile leads to

18.76 percent increase in wage of all the workers at that quantile. The advantage of unconditional quantile regression over the conditional quantile regression is that the conditional quantile regression estimates only the 'within effect'[5] of unionization, whereas the unconditional quantile regression estimates both the 'within' and 'between effect'. The UQPEs at the 10th and 25th quantile have increased around 3 to 4 percent, while at the median, it has decreased approximately 1 percent over the last twenty years.

For women, the UQPE at the lower tail has fallen approximately 2 percent at the 10th quantile and around 5 to 6 percent at the 25th and 50th quantile during the same period. Table 3 shows that the percentage of the high school graduate union workers has decreased from 5.82 to 2.65 percent. The percentages of the college graduate and post college graduate union workers have increased over time leading to more concentration of the union workers at the upper tail of the skill distribution during the last twenty years. As a result, the collective bargaining power of unions for the high school graduate workers has declined over time, leading to fall in average wage gaps between union and nonunion workers around the median during the last two decades.

An important caveat to the interpretation of the UQPE of union status in table 6 is the potential difference between the unobserved heterogeneity of the union and nonunion workers at the upper and lower tail of the wage distribution. Card (2001) shows that if we don't take into account the unobserved heterogeneity, then the estimated marginal effect of union is the true effect plus the self selection effect due to the unobserved skills of union members versus non union workers in the same observed skill group. Card (1996) shows that low skilled workers have higher unobserved skills than their non-union counterparts, contributing to their higher wages. Conversely, high skilled members have below average unobserved skills compared to the non-union workers, explaining the negative wage gap.

[5] Linear conditional quantile regression estimates the effects of unionization only for union workers by using $\beta_{QR} = F_w^{-1}(\tau|union = 1) - F_w^{-1}(\tau|union = 0)$ whereas unconditional quantile regression estimates the effects of unionization for both union and nonunion workers by using $\frac{dq_\tau}{dp} = (Pr[w > q_\tau|union = 1] - Pr[w > q_\tau|union = 0)/f_w(q_\tau)$ where p is the proportion of union workers at the τth quantile and q_τ is the τth population quantile of w.

These previous findings suggest that ignoring the unobserved heterogeneity leads to biased UQPE estimates of unionization for low skilled workers and high skilled workers. In particular, UQPE coefficients have downward bias for the low skilled workers and upward bias for the high skilled workers. This can explain why the unconditional partial effects of unionization at the 90th quantile is negative for both men and women during the period 1990-2010. Firpo et al. (2009) have used the RIF-OLS, RIF-Logit and RIF-NP models to estimate the effects of unionization on the CPS 1983-1985 outgoing rotation group data and found that the unconditional partial effects are negative at the upper tail of the wage distribution. The negative coefficients of the UQPE at the upper tail of the wage distribution are the self selection effect of the high skilled union workers.

To address this issue of unobserved heterogeneity, I follow the approach proposed by DiNardo, Fortin and Lemieux (1996) to decompose the entire wage distribution function by using the Oaxaca decomposition method. The basic idea of this approach is to construct a counterfactual wage distribution function such that all the other workers' characteristics are distributed as in the current period and the distribution of the union workers remains the same as in the previous period. Now subtracting the conterfactual distribution function from the current period distribution function gives us the effects of unionization at different parts of the wage distribution. This is because the only difference between the two distribution functions is the union status of the workers.

The decomposition method takes care of the unobserved heterogeneity between union and non-union workers if we assume that workers in the same income group have similar unobserved heterogeneity. This decomposition method can only compare similar types of workers from the actual and counterfactual wage distribution. There is another implicit assumption we need to make to use this decomposition method: there is no structural shift of the union structure between the the two time periods. If this assumption does not satisfy, then the unobserved heterogeneity of the union workers in the same group differs in the actual and counterfactual distribution. One of the limitations of this paper is that this study does not take into account the role of some potential unobserved factors that cause the changes in the unionization. In fact, this limitation is sustained in the unionization literature. The objective of this study is not to explain what causes unionization, but rather to explain the fall in 50/10 percentile wage gap in the U.S. labor market, given the decline in the unionization over the last two decades.

Card et al. (2003) assume the price of the unobserved skills are not changing over time to find the effect of unionization. To explain the residual wage inequality, Lemieux (2006) assume that the distribution of the unobserved characteristics of the workers is not changing over time. Another way researchers have handled this unobserved heterogeneity problem is by using panel data. Card (1996) and Lemieux (1998) among many others have followed that approach. Panel data estimates of the union wage premium take into account the unobserved heterogeneity by differencing out the time invariant effect on wage. The implicit assumption is that all the unobserved heterogeneities are time invariant. These estimates have measurement error problems and the decomposition method also uses a less restrictive assumption compared to the panel data estimators.

Table 7 represents the effects of unions for men and women over the period 1990-2010 by using the Oaxaca decomposition method. The effects of unionization for men on the 50/10 percentile wage gap is 1.78 percent during the period 1990-2010. This means that in 2010, if union structure remains as in 1990 and everything else remains the same, then the 50/10 percentile wage gap would have 1.78 percent more compared to 2010. This implies that declining unionization can explain the 1.78 percent fall in 50/10 percentile wage gap during the period 1990-2010.

As shown in table 4, during the period 1990-2010, the total number of union members has fallen from 22.99 percent to 15.23 percent and the percentage of the high school graduate union members has fallen from 10.84 percent to 5.37 percent. Combining the high school graduates and workers with some college education contributes around 70 percent of the total fall in unionization over the period 1990-2010. These groups of union workers belong to the middle of the wage distribution. Declining unionization implies that these group of workers' wage falls sharply because as shown in table 6, the marginal effects of union around the median of the wage distribution are 20-23 percent over the period 1990-2010. As a result, the overall wages around the median fall and there is not much change in the wage at the lower tail since unionization has not changed much at the lower tail, compared to the changes in the middle of wage distribution. Combining these two facts leads to a 1.78 percent fall in the 50/10 percentile wage gap during the period 1990-2010.

Figure 7 demonstrates this fact by showing the percentage changes in wages for male and female separately over the period 1990-2010. The left panel shows the changes of wages from the 5th to 95th quantile during the period 2000-2010. Table 3 shows that during the period 1990-2010, the percentage of male high school graduate union workers drops from 10.84 percent to 7.42 percent, and in the right panel of figure 7 we see that the real wages around the median are negative and lower than the wages around the 10th quantile.

During the period 2000-2010, the percentage of male high school graduate union workers again falls from 7.42 to 5.37 percent and the left panel of figure 7 shows the percentage changes in wages around the median are lower compared to the wages at the lower tail of the wage distribution function. The continuous fall of the fraction of the union members around the median also implies that over time, unions have less collective bargaining power for those workers who are at the middle of the wage distribution which is why the Box-Cox unconditional quantile regression partial effects fall from 22.95 percent to 21.97 percent over the period 1990-2010.

For women, unions have almost no effect throughout the wage distribution function. Unionization can explain less than 0.2 percent for both the 50/10 percentile and the 90/50 percentile wage gaps over the period 1990-2010. This is because the changes in the female workers unionization rates are very small and the concentration of union members is at the upper parts of the skill distribution function. Lewis (1986) shows that unions have less bargaining power at the upper tail compared to the rest of the parts of the wage distribution. As a result, the gaps in the overall wage dispersion between union and non-union workers are much smaller for women than men.

3.5 Conclusion

The sources of the asymmetric changes in the U.S. wage distribution with a steady rise in the upper-tail and a stagnation in the lower-tail during the 1990s still remain unresolved. Autor et al. (2008) show that hypotheses, such as falling minimum wages, declining unionization, and skill biased technological change, fail to fully explain the upper-tail inequality paired with declining lower-tail inequality. Alvaredo, Atkinson, Piketty and Saez (2013) show that top tax rates and top pre-tax income share have very high negative correlation over the last 100 years.

Katz and Murphy (1992) and Autor, Katz and Krueger (1998) propose an explanation based on relative demand growth for high skilled workers and fluctuations in relative skill supplies based on canonical supply- demand models. Stories based on return from the human capital variables and demand for skilled labor cannot explain why median income earners are doing worse compared to the workers at the bottom tail of the wage distribution because median income earners have higher levels of human capital variables and skills. Goldin and Katz (2008) show that skilled biased technological change continually increases the demand for high skilled workers. The excess demand for high skilled labor increases the earning gap between the top and bottom tails of the income distribution. Technological changes are measured by changes in the prices of cognitive and non-cognitive skills. This can explain why the 90/50 percentile wage gap is increasing but not why the 50/10 percentile wage gap is falling over time.

The primary objective of this paper is to find out the role of unionization for the changes in the 50/10 percentile and the 90/50 percentile wage gaps for men and women from 1990-2010. I have two main findings on these issues. First, the decline in union membership among men explains around 1.78 percent of the total 8 percent changes in the 50/10 percentile wage gap and does not have much impact on the total 10 percent increases in the 90/50 percentile wage gap over the period 1990-2010. Second, since the fraction of women union members is relatively stable over the last two decades, unionization has no impact on the rise in overall wage inequality.

A secondary goal of this paper is to develop a better understanding of the behavior of the tails of the wage distribution. We show that the decomposition method based on the Linear Quantile Regresion method as proposed by Machoda and Mata (2005) and also the Linear Unconditional Quantile Regression method developed by Firpo, Fortin and Limieux (2009) underestimates the changes in wage at the upper tail of the U.S. wage distribution function. The paper proposes a new estimation method known as 'Box-Cox Unconditional Quantile Regression' to solve this problem. The proposed model is a generalization of the linear unconditional quantile regression and a specific class of non-linear unconditional quantile regression model proposed by Firpo et al. (2009).

Card, Limieux and Riddell (2003) find that unionization can explain around two thirds of the U.S. wage inequality since the early 1980s. My estimates suggest that unionization can explain around 20 to 25 percent of the changes in the lower tail wage inequality and does not have much impact on the upward trend of the 90/50 percentile wage gap over the last two decades. Both of these studies have used different ranges of the U.S. labor market data. However, the estimated impacts of unionization are significantly different. This paper claims that unionization plays a very important role for the changes in U.S. wage inequality over the last two decades, but some other factors like international trade, job offshorability etc. also play crucial roles to explain the downward trend of the lower tail wage inequality. Unionization is then not the dominating factor behind the changes in the U.S. wage inequality as suggested by Card et al. (2003).

Appendix

Proof of Proposition 1

In the Box-Cox model, a small change in t in a covariate X_j corresponds not only a simple location shift of the distribution Y, but also it captures of the effect on the other distributional features. For the sake of simplicity, assume that ϵ follows a distribution F_ϵ. Then the resulting probability response model is,

$$
\begin{aligned}
Pr[Y_\lambda > q_\tau | X = x] &= Pr\left[\frac{(X'\beta_\tau + \epsilon)^\lambda - 1}{\lambda} > q_\tau | X = x\right] \\
&= Pr\left[\epsilon > (1+\lambda q_\tau)^{1/\lambda} - X'\beta_\tau | X = x\right] \\
&= Pr\left[\epsilon > (1+\lambda q_\tau)^{1/\lambda} - X'\beta_\tau | X = x\right] \\
&= 1 - F_\epsilon\left[(1+\lambda q_\tau)^{1/\lambda} - X'\beta_\tau | X = x\right]
\end{aligned}
$$

Thus if ϵ was normally distributed, the probability response model would be a standard probit model. Taking derivative with respect to X yields,

$$
\frac{dPr[Y_\lambda > q_\tau | X = x]}{dX} = \beta_\tau \times f_\epsilon\left((1+\lambda q_\tau)^{1/\lambda} - X'\beta_\tau\right)
$$

where $f_\epsilon(\cdot)$ as the density of ϵ and the marginal effects are obtained by integrating over the distribution of X. The average marginal effect is

$$
\int \frac{dPr[Y_\lambda > q_\tau | X = x]}{dX} dF_X(x) = \beta_\tau \int f_\epsilon\left((1+\lambda q_\tau)^{1/\lambda} - X'\beta_\tau\right) dF_X(x)
$$

We can rewrite $f_Y(q_\tau)$ as,

$$
\begin{aligned}
f_Y(q_\tau) &= \frac{d}{dq_\tau}(F_Y(q_\tau)) \\
&= \frac{d}{dq_\tau}[Y \leq q_\tau(x)] \\
&= \frac{dE}{dq_\tau}\left[Pr(\frac{(X'\beta_\tau + \epsilon)^\lambda_\tau - 1}{\lambda_\tau} \leq q \mid X = x)\right] \\
&= \frac{dE}{dq_\tau}\left[Pr(\epsilon \leq (1 + \lambda q_\tau)^{1/\lambda_\tau} - X'\beta_\tau \mid X = x)\right] \\
&= \frac{dE}{dq_\tau}\left[F_\epsilon\left((1 + \lambda_\tau q_\tau)^{1/\lambda_\tau} - X'\beta_\tau\right)\right] \\
&= E\left[f_\epsilon(\cdot) \times \frac{1}{\lambda_\tau}(1 + \lambda_\tau q_\tau)^{(1/\lambda_\tau)-1} \times \lambda_\tau\right] \\
&= \left((1 + \lambda_\tau q_\tau)^{(1-\lambda_\tau)/\lambda_\tau}\right) E\left[f_\epsilon\left((1 + \lambda_\tau q_\tau)^{1/\lambda_\tau} - X'\beta_\tau\right)\right] \\
&= \left((1 + \lambda_\tau q_\tau)^{(1-\lambda_\tau)/\lambda_\tau}\right) \int f_\epsilon\left((1 + \lambda_\tau q_\tau)^{1/\lambda_\tau} - X'\beta_\tau\right) dF_X(x)
\end{aligned}
$$

The Unconditional Quantile Partial Effect for the Box-Cox model is given by,

$$
\begin{aligned}
UQPE &= \frac{\beta_\tau \int f_\epsilon\left((1 + \lambda q_\tau)^{1/\lambda} - X'\beta_\tau\right) dF_X(x)}{((1 + \lambda_\tau q_\tau)^{(1-\lambda_\tau)/\lambda_\tau}) \int f_\epsilon\left((1 + \lambda_\tau q_\tau)^{1/\lambda_\tau} - X'\beta_\tau\right) dF_X(x)} \\
&= \beta_\tau(1 + \lambda_\tau q_\tau)^{(\lambda_\tau - 1)/\lambda_\tau}
\end{aligned}
$$

Proof of Proposition 2

Again Firpo, Fortin and Lemieux (2009) show that there exists a close relation between the unconditional partial effects (α_{F_Y}) and RIF regression function m_τ. This can be represented as,

$$\begin{aligned}
&E\left[\frac{dE[RIF(y,q_\tau)|X=x]}{dx}\right] = \alpha_{F_Y}(X=x,q_\tau) \\
&\Rightarrow \int \frac{dE[RIF(y,q_\tau)|X=x]}{dx} dF_X = \beta_\tau(1+\lambda_\tau q_\tau)^{(1-\lambda_\tau)/\lambda_\tau}
\end{aligned}$$

we substitute RIF regression function $m_\tau = E[RIF(y,q_\tau)|X=x]$ in the above relation and get,

$$\begin{aligned}
&\int \frac{dm_\tau}{dx} dF_X = \beta_\tau(1+\lambda_\tau q_\tau)^{(1-\lambda_\tau)/\lambda_\tau} \\
&\Rightarrow \int dm_\tau \int dF_X = \int \beta_\tau(1+\lambda_\tau q_\tau)^{(1-\lambda_\tau)/\lambda_\tau} dX \\
&\Rightarrow m_\tau = X'\beta_\tau(1+\lambda_\tau q_\tau)^{(\lambda_\tau-1)/\lambda_\tau}
\end{aligned}$$

Graphs and Tables

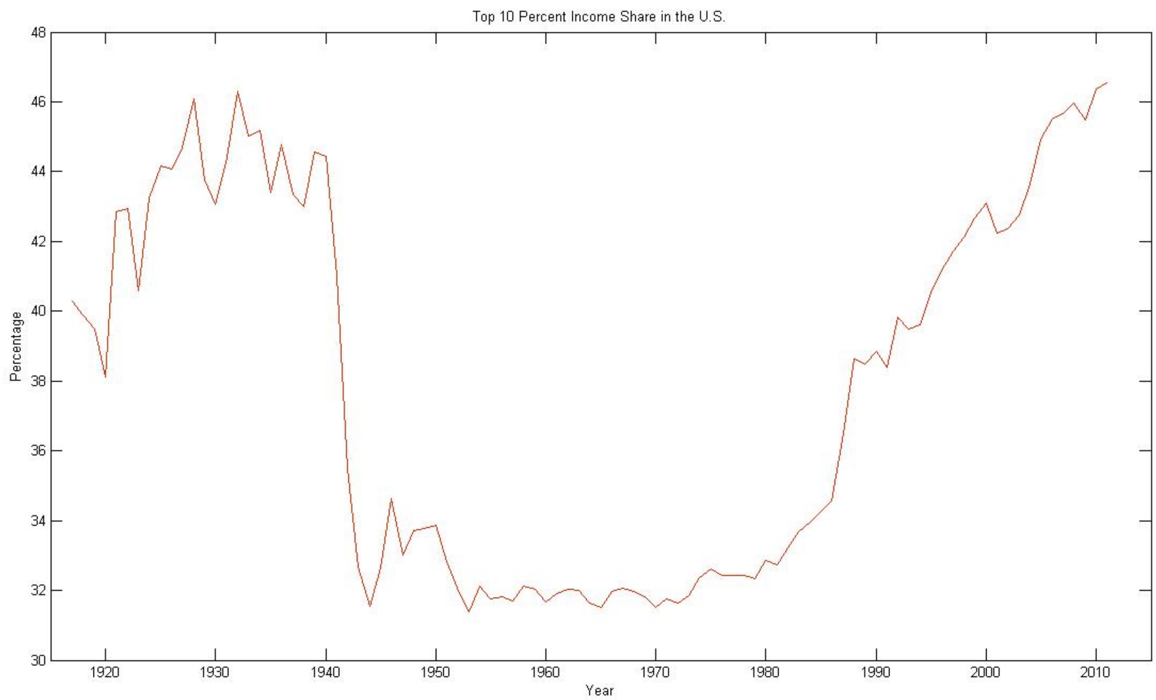

Figure 3.1: Top 10 Percent Income Share in the United States from 1913-2012

Figure 2 : 90/10, 90/50 and 50/10 Percentile Wage Gap in the Period 1975-2012

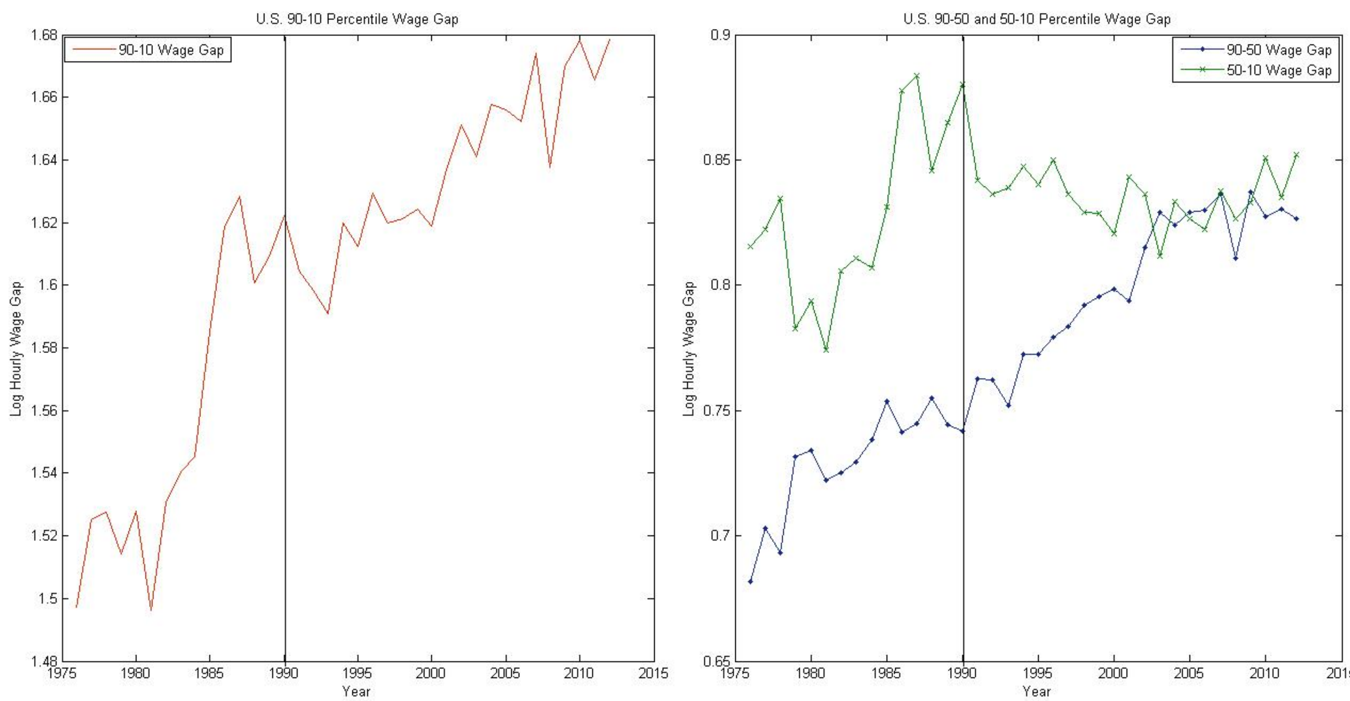

Figure 3.2: 90/10, 90/50 and 50/10 Percentile Wage Gap in the Period 1975-2012

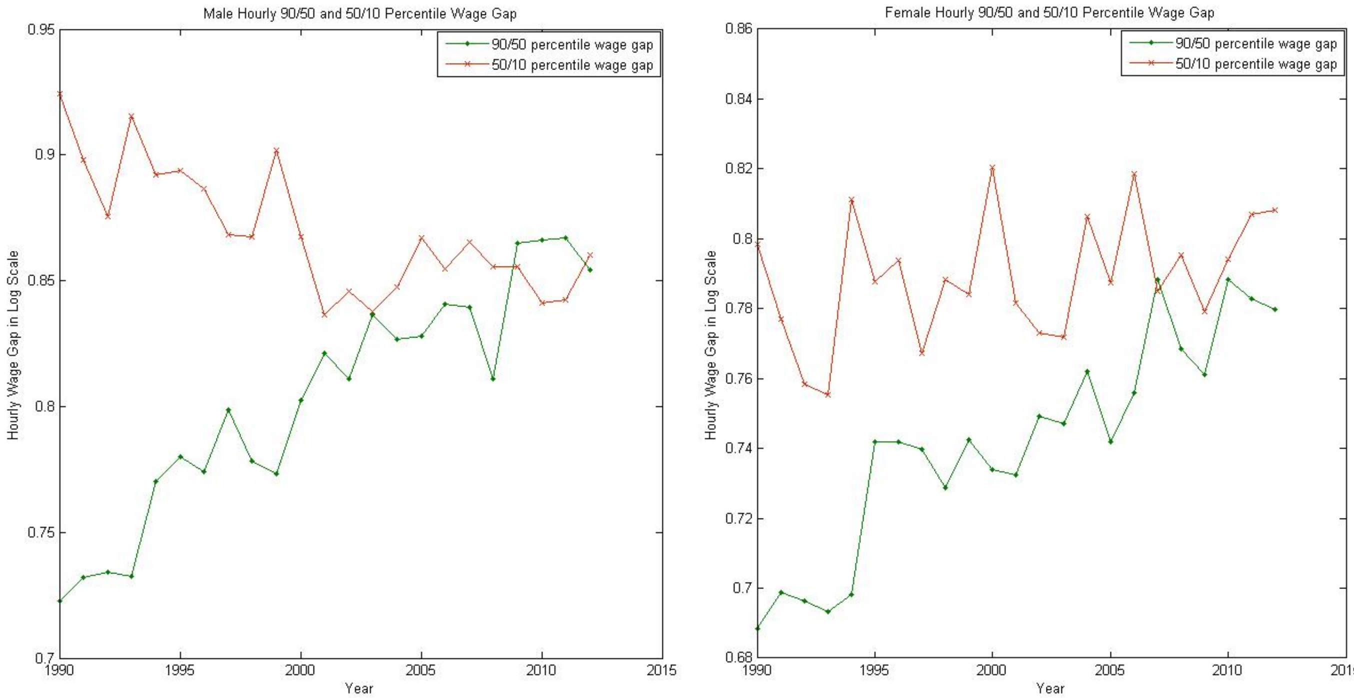

Figure 3.3: 90/50 and 50/10 Male Female Percentile Wage Gap over the Period 1990-2012

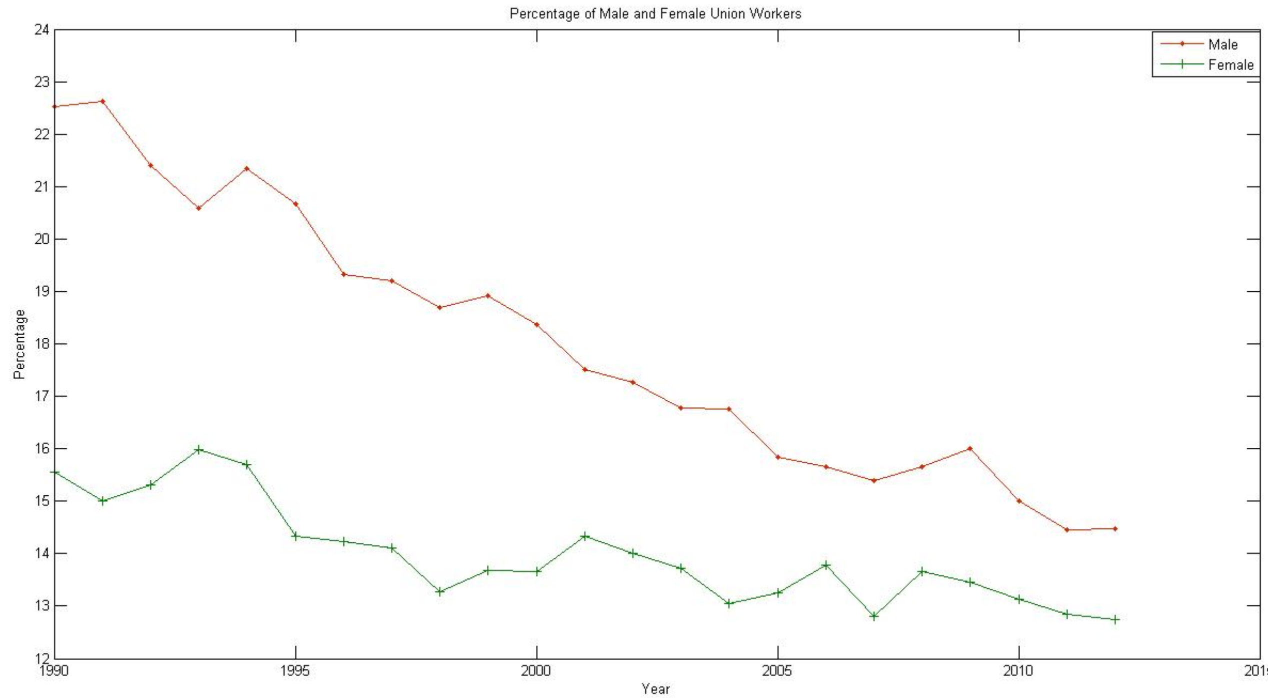

Figure 3.4: Percentage of Male Female Union Workers over the Period 1990-2012

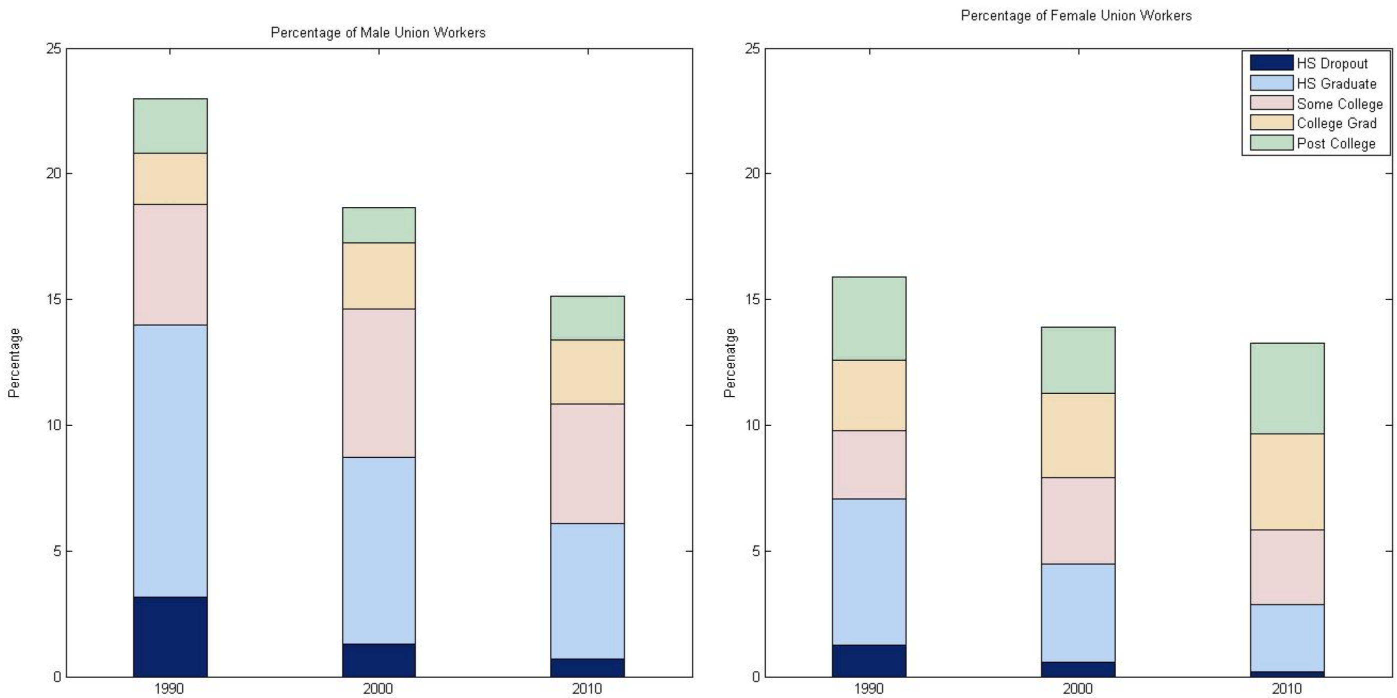

Figure 3.5: Decomposition of Male and Female Union Workers by Education

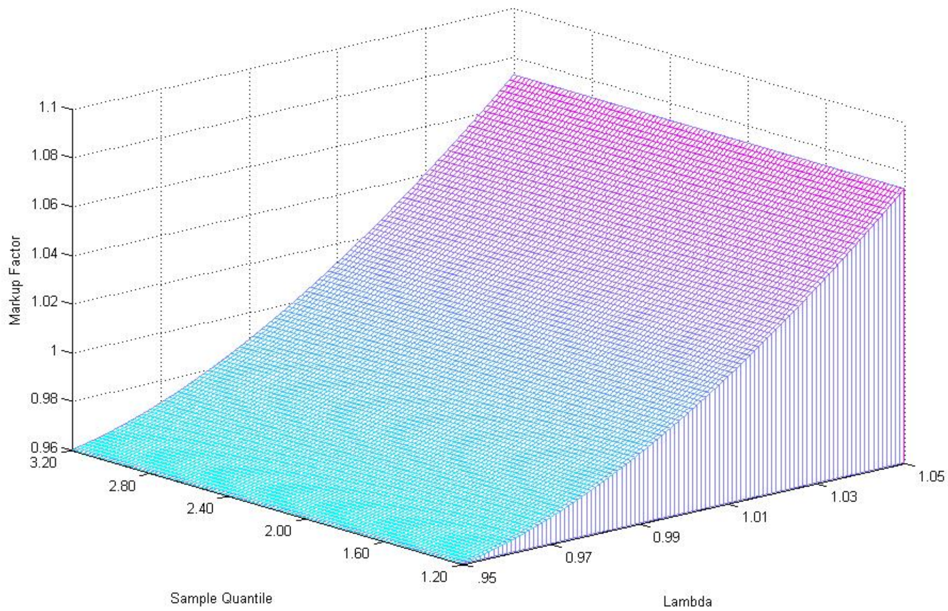

Figure 3.6: Plot of the Markup Factor $(1 + \lambda_\tau q_\tau)^{(\lambda_\tau - 1)/\lambda_\tau}$

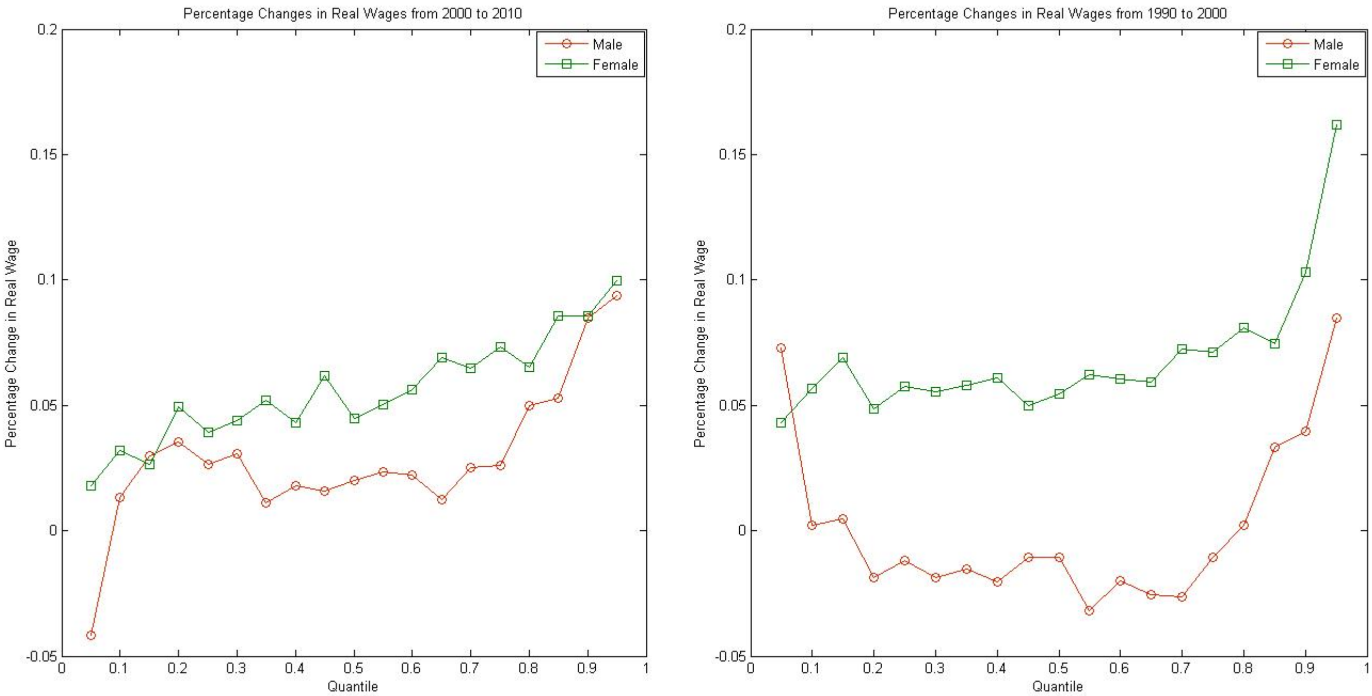

Figure 3.7: Changes in the Unconditional Male and Female Wage Distribution from 1990-2010

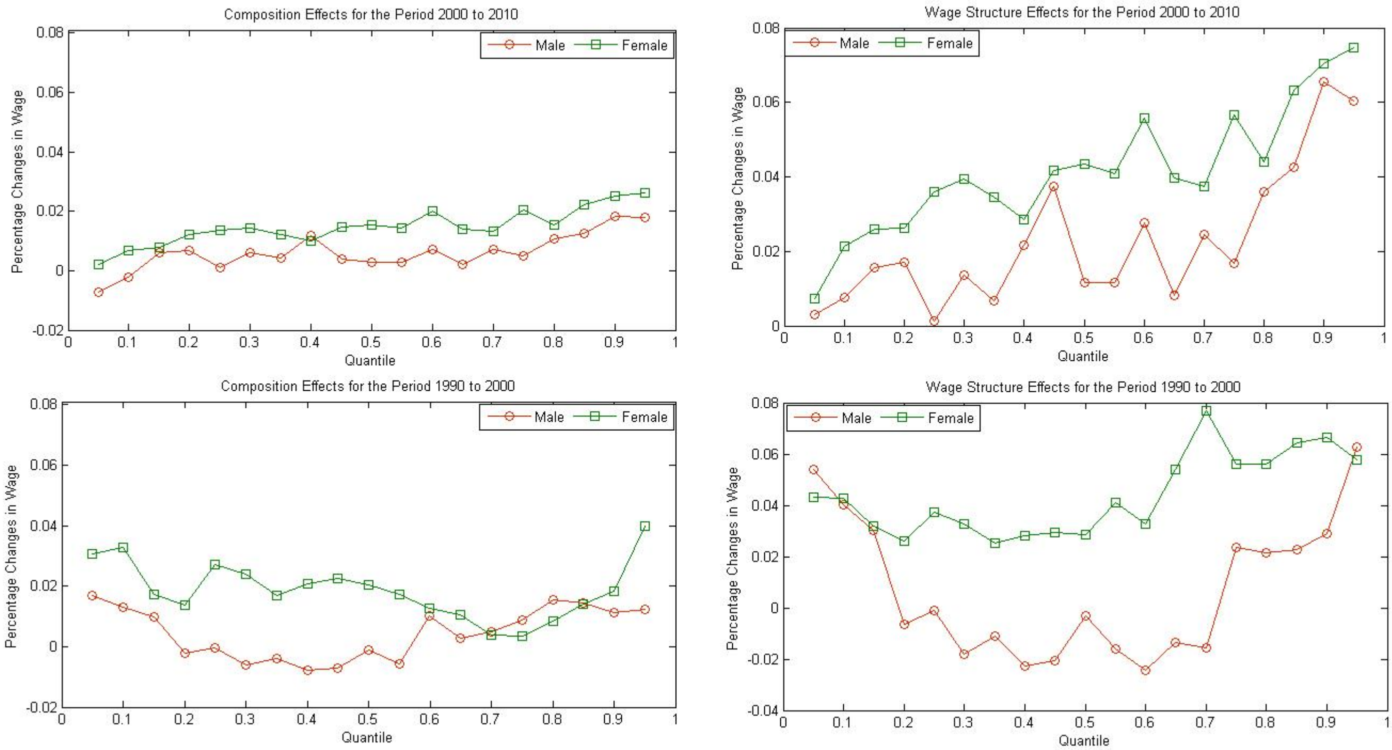

Figure 3.8: Decomposition of Male Female Wage Distribution Function for the Period 1990-2010

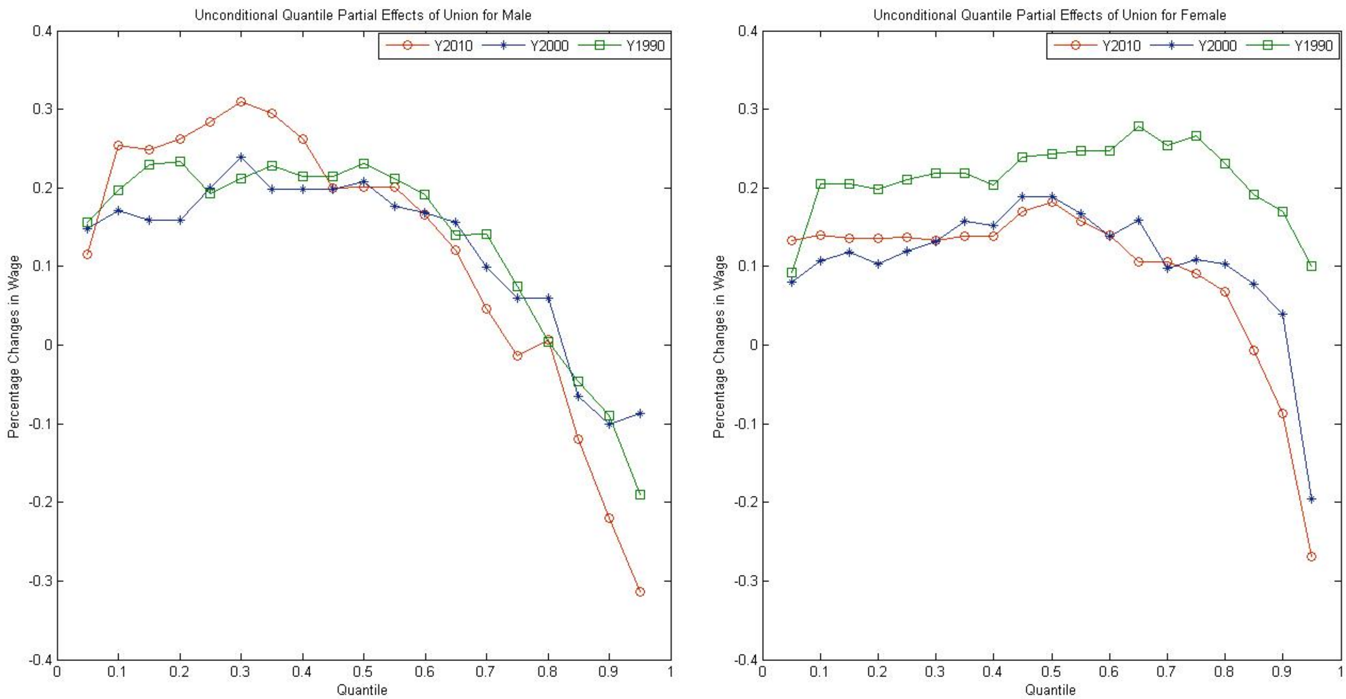

Figure 3.9: Unconditional Partial Effects of Union for the Period 1990-2010

Table 3.1: Summary Statistics of Current Population Survey Data for All

Variable	Year 2010	Year 2000	Year 1990
No of Obs	84,239	59,750	69,651
Male	51.35%	51.89%	52.61%
Union	14.18%	16.33%	19.58%
Black	12.06%	9.96%	9.40%
Married	61.79%	61.41%	63.39%
Urban	75.05%	75.11%	72.50%
Skilled Lab	30.89%	25.73%	22.62%
Schooling (Avg)	13.6973	13.2727	13.0485
Experience(Avg)	20.6494	19.5379	18.0073
Hourly Log Wage (Avg)	2.8277	2.7812	2.7477

Table 3.2: Summary Statistics (Mean and Standard Deviation) of Current Population Survey Data for Male and Female

		Male			Female		
Variable	Stats	2010	2000	1990	2010	2000	1990
Union	Mean	0.1513	0.1867	0.2300	0.1324	0.1389	0.1590
	SD	0.3584	0.3897	0.4208	0.3390	0.3459	0.3657
Black	Mean	0.1043	0.0857	0.0821	0.1379	0.1147	0.1072
	SD	0.3056	0.2800	0.2745	0.3448	0.3186	0.3094
Married	Mean	0.6421	0.6332	0.6536	0.5924	0.5935	0.6120
	SD	0.4794	0.4819	0.4758	0.4914	0.4912	0.4873
Urban	Mean	0.7542	0.7528	0.7283	0.7468	0.7493	0.7215
	SD	0.4306	0.4314	0.4449	0.4348	0.4334	0.4483
Education	Mean	13.5185	13.1745	13.0246	13.8863	13.3787	13.0751
	SD	2.9222	3.0590	3.0600	2.6735	2.6765	2.6363
Age	Mean	40.3410	38.7596	37.1964	40.3529	38.8658	36.8999
	SD	12.2458	11.9745	12.1274	12.2638	11.9323	12.0129
Experience	Mean	20.8226	19.5851	18.1718	20.4666	19.4870	17.8248
	SD	12.1789	11.9360	12.3512	12.3851	12.0782	12.3711
Log Wage	Mean	2.9423	2.9074	2.8993	2.7068	2.6453	2.5796
(Hourly)	SD	0.7430	0.7080	0.6756	0.6961	0.6701	0.6259
No of Obs		43,263	31,009	36,645	40,976	28,741	33,006

Table 3.3: Composition of Union Workers by Education Level and Percentage Wage Gap between Union and Non-union Workers

	Male			Female		
Education	2010	2000	1990	2010	2000	1990
HS Dropout						
Union Workers(%)	0.7189	1.3110	3.1544	0.2055	0.5693	1.2449
Wage Gap (%)	57.0626	37.4755	35.2199	10.2920	29.9023	29.5490
HS Grad						
Union Workers(%)	5.3748	7.4237	10.8416	2.6554	3.8992	5.8242
Wage Gap (%)	28.0074	27.5904	33.4475	20.2451	17.8301	24.2174
Some College						
Union Workers(%)	4.7415	5.8669	4.7978	2.9638	3.4334	2.7332
Wage Gap (%)	30.8344	27.1019	29.4737	19.2739	17.9106	27.6953
College Grad						
Union Workers(%)	2.5504	2.6384	2.0410	3.8375	3.3816	2.7761
Wage Gap (%)	−3.3531	1.6807	7.5176	15.6758	5.9849	15.7740
Post College						
Union Workers(%)	1.7459	1.4257	2.1603	3.5806	2.6052	3.3199
Wage Gap (%)	−16.5677	−13.7225	1.5243	−2.6219	3.2816	14.1314
Total Union Workers in Lab Market (%)	15.1318	18.6660	22.9953	13.2431	13.8888	15.8986

Table 3.4: Change in Unconditional Wage Distribution from 1990-2010

Male

Index	2010	2000	1990	Δ 2010-2000	Δ 2000-1990
10th quant	2.0399	2.0264	2.0195	0.0135	0.0068
	$(2.0384, 2.0417)$	$(2.0247, 2.0293)$	$(2.0168, 2.0212)$	$(0.0106, 0.0162)$	$(0.0042, 0.0098)$
25th quant	2.4850	2.4523	2.4744	0.0327	-0.0220
	$(2.4839, 2.4857)$	$(2.4498, 2.4549)$	$(2.4725, 2.4762)$	$(0.0300, 0.0351)$	$(-0.0256, -0.01829)$
50th quant	2.9565	2.9320	2.9409	0.0244	-0.0088
	$(2.9551, 2.9669)$	$(2.9301, 2.9337)$	$(2.9399, 2.9429)$	$(0.0229, 0.0263)$	$(-0.0113, -0.0072)$
75th quant	3.3839	3.3531	3.3662	0.0308	-0.0131
	$(3.3816, 3.3860)$	$(3.3512, 3.3553)$	$(3.3649, 3.3677)$	$(0.0274, 0.0339)$	$(-0.0158, -0.0107)$
90th quant	3.8249	3.7372	3.7014	0.0877	0.0357
	$(3.8213, 3.8273)$	$(3.7354, 3.7394)$	$(3.6987, 3.7029)$	$(0.0853, 0.0923)$	$(0.0330, 0.0385)$
Gini coeff	0.1387	0.13648	0.1300	0.0022	0.0063
	$(0.1382, 0.1411)$	$(0.1353, 0.13865)$	$(0.1290, 0.1311)$	$(-0.0014, 0.0046)$	$(0.0047, 0.0083)$

Female

Index	2010	2000	1990	Δ 2010-2000	Δ 2000-1990
10th quant	1.8875	1.8475	1.7943	0.0400	0.0531
	$(1.8847, 1.8899)$	$(1.8457, 1.8496)$	$(1.7930, 1.7960)$	$(0.0358, 0.0427)$	$(0.0506, 0.0559)$
25th quant	2.2643	2.2326	2.1762	0.0317	0.0563
	$(2.2635, 2.2656)$	$(2.2304, 2.2344)$	$(2.1741, 2.1787)$	$(0.0293, 0.0338)$	$(0.0537, 0.0595)$
50th quant	2.6186	2.6431	2.5958	0.0538	0.0473
	$(2.6945, 2.6996)$	$(2.6408, 2.6457)$	$(2.5942, 2.5972)$	$(0.0487, 0.0566)$	$(0.0450, 0.0515)$
75th quant	3.0412	3.0687	2.9973	0.0718	0.0713
	$(3.1382, 3.1424)$	$(3.0670, 3.0711)$	$(2.9954, 2.9996)$	$(0.0687, 0.0744)$	$(0.0689, 0.0743)$
90th quant	3.4571	3.4483	3.3455	0.0921	0.1028
	$(3.5381, 3.5435)$	$(3.4469, 3.3430)$	$(3.3430, 3.3472)$	$(0.0888, 0.0942)$	$(0.0998, 0.1047)$
Gini coeff	0.1410	0.1399	0.1347	0.0011	0.0051
	$(0.1389, 0.1433)$	$(0.1377, 0.1424)$	$(0.1293, 0.1374)$	$(-0.0010, 0.0039)$	$(0.0012, 0.0080)$

Table 3.5: Decomposition of Wage Distribution Function over the Period 1990-2010

Male

	Δ 2010-2000			Δ 2000-1990		
Index	Composition	Wage Structure	Residual	Composition	Wage Structure	Residual
10th quant	-0.0007	-0.0025	0.0168	0.0051	0.0188	-0.0171
	$(-0.0016, 0.0030)$	$(-0.0048, 0.0000)$	$(0.0138, 0.0208)$	$(0.0044, 0.0060)$	$(0.0158, 0.0228)$	$(-0.0214, -0.0140)$
25th quant	0.0023	0.0066	0.0237	-0.0020	-0.0057	-0.0142
	$(0.0016, 0.0030)$	$(0.0046, -0.0086)$	$(0.0207, 0.0261)$	$(-0.0027, -0.0012)$	$(-0.0078, -0.0037)$	$(-0.0174, -0.0112)$
50th quant	0.0044	0.0142	0.0057	-0.0023	-0.0068	0.0003
	$(0.0039, 0.0049)$	$(0.0127, 0.0156)$	$(0.0034, 0.0078)$	$(-0.0030, -0.0019)$	$(-0.0083, -0.0047)$	$(-0.0021, 0.0021)$
75th quant	0.0056	0.0171	0.0080	-0.0030	-0.0088	-0.0013
	$(0.0048, 0.0062)$	$(0.0152, 0.0191)$	$(0.0063, 0.0102)$	$(-0.0035, -0.0025)$	$(-0.0104, -0.0076)$	$(-0.0033, 0.0007)$
90th quant	0.0195	0.0618	0.0063	0.0093	0.0312	-0.0049
	$(0.0187, 0.0203)$	$(0.0590, 0.0636)$	$(0.0028, 0.0084)$	$(0.0087, 0.0098)$	$(0.0293, 0.0338)$	$(-0.0081, -0.0024)$
Gini coeff	-0.0003	-0.0003	0.0039	0.0001	0.0001	0.0040
	$(-0.0005, -0.0000)$	$-(0.0006, -0.0001)$	$(0.0035, 0.0045)$	$(-0.0000, 0.0003)$	$(-0.000, 0.0004)$	$(0.0033, 0.0044)$

Female

	Δ 2010-2000			Δ 2000-1990		
Index	Composition	Wage Structure	Residual	Composition	Wage Structure	Residual
10th quant	0.0068	0.0215	0.0116	0.0287	0.0440	-0.0197
	$(0.0062, 0.0075)$	$(0.0177, 0.0232)$	$(0.0087, 0.0145)$	$(0.0267, 0.0312)$	$(0.0427, 0.0451)$	$(-0.0225, -0.0170)$
25th quant	0.0115	0.0316	-0.0114	0.0243	0.0382	-0.0062
	$(0.0104, 0.0121)$	$(0.0299, 0.0329)$	$(-0.0138, -0.0087)$	$(0.0231, 0.0253)$	$(0.0375, 0.0392)$	$(-0.0086, -0.0031)$
50th quant	0.0160	0.0453	-0.0075	0.0195	0.0253	0.0024
	$(0.0154, 0.0168)$	$(0.0437, 0.0472)$	$(-0.0101, -0.0057)$	$(0.0183, 0.0208)$	$(0.0245, 0.0267)$	$(0.0003, 0.0044)$
75th quant	0.0197	0.0552	-0.0031	0.0032	0.0575	0.0106
	$(0.0190, 0.0204)$	$(0.0531, 0.0567)$	$(-0.0057, -0.0006)$	$(0.0029, 0.0036)$	$(0.05525, 0.0605)$	$(0.0084, 0.0138)$
90th quant	0.0254	0.0718	-0.0052	0.0185	0.6593	-0.5750
	$(0.0247, 0.0269)$	$(0.0695, 0.0747)$	$(-0.0084, -0.0024)$	$(0.0175, 0.0192)$	$(0.6576, 0.6605)$	$(-0.5764, -0.5733)$
Gini coeff	0.0003	0.0003	0.0023	-0.0002	-0.0000	0.0023
	$(0.0000, 0.0008)$	$(0.0000, 0.0007)$	$(0.0016, 0.0032)$	$(-0.0011, 0.0012)$	$(-0.0004, 0.0005)$	$(-0.0003, 0.0035)$

Table 3.6: Box-Cox Unconditional Quantile Partial Effects of Unionization from 1990-2010

Index	Year	10th quant	25th quant	50th quant	75th quant	90th quant
Male						
	Year 2010	0.2262	0.2470	0.2197	0.0088	-0.2037
		$(0.2175, 0.2377)$	$(0.2392, 0.2557)$	$(0.2118, 0.2266)$	$(-0.0023, 02133)$	$(-0.2196, -0.1936)$
	Year 2000	0.1873	0.2129	0.2203	0.0599	-0.0837
		$(0.1818, 0.1945)$	$(0.2050, 0.2191)$	$(0.2133, 0.2303)$	$(0.0530, 0.0713)$	$(-0.0946, -0.0750)$
	Year 1990	0.1876	0.2172	0.2295	0.1076	-0.0449
		$(0.1819, 0.2096)$	$(0.2096, 0.2241)$	$(0.2242, 0.2356)$	$(0.1021, 0.1201)$	$(-0.0515, -0.0347)$
Female						
	Year 2010	0.1568	0.1592	0.1800	0.1071	-0.0437
		$(0.1489, 0.1648)$	$(0.1517, 0.17054)$	$(0.1720, 0.1877)$	$(0.0909, 0.1192)$	$(-0.0606, -0.0294)$
	Year 2000	0.1049	0.1104	0.1739	0.1146	0.0138
		$(0.0955, 0.1138)$	$(1042, 0.1174)$	$(0.1678, 0.1838)$	$(0.1044, 0.1269)$	$(-0.0066, 0.0262)$
	Year 1990	0.1797	0.2139	0.2423	0.2434	0.1380
		$(0.1710, 0.1859)$	$(0.2076, 0.2197)$	$(0.2376, 0.2483)$	$(0.2347, 0.2549)$	$(0.1257, 0.1476)$

Table 3.7: Linear Quantile Regression Marginal Effects of Unionization from 1990-2010

Index	Year	10th quant	25th quant	50th quant	75th quant	90th quant
Male						
	Year 2010	0.2343	0.1746	0.1011	-0.0049	-0.0404
		$(0.2089, 0.2658)$	$(0.1803, 0.2014)$	$(0.0992, 0.1219)$	$(-0.0140, -0.0009)$	$(-0.0493, -0.0274)$
	Year 2000	0.1966	0.1139	0.1027	0.0690	-0.0246
		$(0.1810, 0.2047)$	$(0.1065, 0.1213)$	$(0.0936, 0.1127)$	$(0.0621, 0.0755)$	$(-0.0352, -0.0139)$
	Year 1990	0.1922	0.1276	0.1086	0.0841	0.0398
		$(0.1795, 0.2047)$	$(0.1181, 0.1394)$	$(0.1017, 0.1146)$	$(0.0777, 0.0894)$	$(0.0343, 0.0467)$
Female						
	Year 2010	0.3228	0.1703	0.0637	0.0531	0.0177
		$(0.2856, 0.3560)$	$(0.1545, 0.1846)$	$(0.0540, 0.0744)$	$(0.0442, 0.0692)$	$(0.0023, 0.0394)$
	Year 2000	0.2540	0.1676	0.0801	0.0314	0.0012
		$(0.2371, 0.2656)$	$(0.1570, 0.1775)$	$(0.0672, 0.1059)$	$(0.0211, 0.0401)$	$(-0.0074, 0.0097)$
	Year 1990	0.3006	0.2687	0.1868	0.1028	0.0347
		$(0.2937, 0.3101)$	$(0.2574, 0.2768)$	$(0.1830, 0.1919)$	$(0.0990, 0.1083)$	$(0.0295, 0.0519)$

Table 3.8: Effects of Declining Unionization on Wage Inequality Over the Period 1990-2010

Year 1990-2010

	50/10 Percentile Wage Gap	90/50 Percentile Wage Gap
Male		
	0.0178	0.0035
	(0.0177, 0.0179)	(0.0034, 0.0036)
Female		
	−0.0009	−0.0010
	(−0.0010, −0.0008)	(−0.0011, −0.0009)

⋆ The numbers in the table show the hourly log wage gaps of different percentiles between the counterfactual wages and the actual 2010 wages. Counterfactual wage is defined as if the distribution of union workers is same in 1990 and workers' all other characteristics remain the same in 2010 and workers are paid according to the 2010 market prices. The numbers in the parentheses represent the 95 percent bootstrap confidence interval for 100 replications.

CHAPTER IV

Sorting in the Labor Market Based on Workers' Noncognitive Skills

4.1 Introduction

A large number of studies focus on the role of cognitive and noncognitive skills on the individual labor market outcomes. The main implication of the equalizing differences theory is that in the labor market, workers sort out their occupations based on their preferences over the different job characteristics. Workers who are in teaching and nursing occupations need to be relatively caring in dealing with people and patients. Managers need to have relatively more resource management skills. Similarly scientist need be good at analyzing information. Krueger and Schkade (2008) find that workers who are more gregarious, based on their behavior off the job, tend to choose the jobs that involve more social interaction.

This study presents evidences on whether workers sort out their occupations based on their preference over the job characteristics and their noncognitive skills. This motivation of this paper is to explain the recent trends of the gender and racial wage gaps since previous studies showed that labor market sorting behavior plays a very important role to explain the gender and racial wage gap. Numerous studies focus on the role of cognitive skills on schooling and wages and noncognitive skills on individual labor market outcome such as labor market success but there are not many studies attempt to explain the labor market sorting behavior based on workers' cognitive and noncognitive skills. Krueger and Schkade (2008) points out that the extent of workers' sorting by preferences has implications for many labor market policies and for economic theory.

The classical labor market wage equilibrium model ignores the fact that the equilibrium wage is the sum of two distinct transactions, one for labor services and workers characteristics, and another for job attributes. The theory of equalizing differences take into account that workers pay a positive price for preferred job characteristics and the price paid by the employers to induce workers to undertake some undesirable tasks takes the form of a wage premium, a negative price for the job. Rosen (1986) shows that the observed distribution of wages clears both markets, overall job characteristics and job attributes under the assumption of perfect information on both sides of the market. This suggest that in the theory of equalizing differences, labor market can be viewed as an implicit market of job characteristics and worker's attributes and the resulting market equilibrium associates a wage for each job task.

Heckman, Stixrud and Urzua (2006) propose a theoretical occupational choice model based on worker's cognitive and noncognitive skills. Instead of using different occupational choice as the outcome variable, Heckman et al. (2006) use the latent utility associated with choosing a white collar occupation or blue collar occupation. This paper uses a different approach compared to the Heckman et al. (2006) model and follows the basic framework of equalizing differences to explain the labor market sorting mechanism. Rosen's (1986) model can explain why an individual worker accepts a less attractive job in terms of wage by incorporating the monetary compensation of undesirable job characteristics. However, this model cannot explain what induces workers' preferences over job characteristics. This paper proposes an extension of Rosen's (1986) basic model of equalizing differences by explaining the role of noncognitive skills on worker's job preferences to explain the labor market sorting behavior.

This paper proposes a one period static model where job characteristics are given to any individual worker. The representative worker's preference over those job characteristics depends on his/her given level of cognitive and noncognitive skills. For example, a high skilled introvert worker who enjoys working independently on challenging cognitive problem may not choose an occupation which requires frequent interaction with co-workers or customers. Similarly, a low skilled extrovert workers prefers an occupation which requires relatively more social interaction.

Individuals vary in their stock of cognitive and noncognitive skills and jobs differ in terms of the task levels in the proposed model. High skilled workers have higher job satisfaction in the occupations which require higher level of cognitive skills to perform a given task in the proposed model. The model assumes that an individual worker has perfect information on his/her stock of cognitive and noncognitive skills, task level and other job characteristics of any job, and the wage differential between given any two jobs. Potential employers also have full information to perfectly determine which worker can perform the task level assigned in a given job. As a result, apart from this worker's job preferences, the equilibrium employment also depends on the observed wage differentials to equalize the total monetary compensation of job activities that are differentiate by various attributes- working environments, worker skills and other job requirements.

Labor market sorting behavior plays an important role why in the U.S. labor market male-female wage gap is shrinking over time, especially at the upper tail of the income distribution, while the black-white wage gap remains steady during the 2000s. Filer (1983) argues that personality plays an important role in explaining labor market outcomes and gender wage differentials. Borghans, Weel and Weinberg (2006) investigate whether changes in the importance of the noncognitive skills can explain why women's wage increased more rapidly, while the wages of black grew more slowly over these years relative to earlier years in the U.S. labor market during the period of the late 1970s to the early 1990s.

Bertrand and Hallock (2001), Goldin (2004) find that the growth of a wide variety of white collar jobs combined with the greater ability of women to hold certain professional jobs help to reduce the gender wage gap. Weinberg (2000) shows that computerization of the labor market has taken away some of the physical disadvantages women had in a non-computerized labor market. By using two single-cohort longitudinal surveys data, Fortin (2006) investigates the impact of greed, ambition, leadership, altruism, gender role attitudes, family values and income expectations on the gender gap and finds that some of these soft skills have significant impact while others do not. Bayard et al. (2003) show that in the U.S. labor market, a major portion of the male-female wage gap can be explained by the segregation of women into the lower-paying occupations, industries, establishments and occupations within establishments during the 1990s.

By using the Current Population Survey (CPS) data, this paper shows that the relative employment share of women is higher in the occupations in which people tasks are more important. The reverse is true for black workers. Becker (1971), Holzer and Ihlanfeldt (1998) propose the hypothesis that racial, ethnic, linguistic, and cultural differences interfere with the performance of people tasks because of two possible reasons. First, the members of such minority groups are less able to interact with members of the majority groups and second, the co-workers or the customers are prejudiced toward minority groups.

This paper focuses on how workers sort out their occupations based on their noncognitive skills by using the O*NET and CPS data. O*NET data classifies noncognitive skills in different sub categories and allow us to investigate which types of noncognitive skills have significant impact on different types of occupation. Additionally, this paper also shows the labor market sorting results by gender and race. These labor marketing sorting mechanism by subgroups helps us to understand how occupational choice plays an important role to explain male-female and black-white wage gaps in the U.S. labor market.

This paper proposes a simple extension of Rosen's (1986) basic framework of equalizing differences model. Estimated marginal effects of different types of noncognitive skills to choose occupations such as clerical and sales, and service with respect to the occupation professional, managerial and technical are almost always greater than 1 in a multinominal logit model. The results also vary over gender and race. It is shown that female workers prefer to choose the occupations which require more social interactions. These results complement those in recent work by Krueger and Schkade (2008), who find that workers who have higher social skills tend to choose the jobs which involve frequent social interaction.

The paper is constructed as follows. Section 2 represents the sorting mechanism model. In section 3, I describes the data from two different data sources and the construction of the noncognitive measure. Section 4 provides the main results of this paper. I conclude in section 5.

4.2 Economic Model

We start with a equilibrium wage setting model where wage not only depends on workers human capital but also depends on the workers' occupation given the other demographic characteristics. In this set up, the wage equation is given by:

$$w = w(z, \theta | X = x) \tag{4.1}$$

where z is the human capital stock, θ denotes the occupation and X is the set of other demographic variables related to wage.

In this model, occupation has been defined by task level, and to perform that task level, workers need to have certain skills. Acemoglu and Autor (2011) define task as a unit of work activity that produces output (goods and services), whereas skill is a worker's endowment of capabilities for performing various tasks. The distinction between skill and tasks becomes particularly relevant when workers of a given skill level can perform a variety of tasks. In a dynamic wage setting model, the set of task workers perform depends on the labor market conditions, such as technology.

Each job has different tasks and occupation is a collection of different jobs. To simplify the model, I assume every occupation has only one job. The model can be easily generalised for multiple jobs in a single occupation. Each occupation then has some job characteristics based on the tasks. Job characteristics are fixed for any given period in a static model. However, in a multi-period dynamic model, job characteristics depend on the task level through the technological changes. It is assumed that job characteristics are given to any worker and workers make their optimal choices based on that given conditions.

We borrow from Cunha and Heckman's (2007, 2008) model of human capital formation based on cognitive and noncognitive skills given the early childhood investment by parents (I_p):

$$z = z(z_c, z_{nc}|I_p) \tag{4.2}$$

Cunha and Heckman (2008) considered a general model where cognitive skills can promote the formation of the noncognitive skills and vice-versa. In this model we do not observe the parental investment I_p, as a result the level of cognitive skills (z_c) and noncognitive skills (z_{nc}) for any worker is fixed when a worker enters into the labor market. The stock of z_c and z_{nc} also develops during on the job training.

4.2.1 Job Preference Function

In this model, each worker has preference over the job characteristics. In the labor market sorting literature we implicitly assume that this individuals job preference function are independent of their cognitive and noncognitive skills. The proposed model relaxes this assumption. The individual job preference function has the following implicit functional form:

$$\tau_i = \tau(z_c^i, z_{nc}^i|\eta_j) \tag{4.3}$$

where τ_i is the ith person's job preference function and η_j is the set of job characteristics of the jth occupation. We define η_j as:

$$\eta_j = \eta_j(\eta_{j1}, \eta_{j2}, ..., \eta_{jk}) \tag{4.4}$$

where these job characteristics are functions of task level. In a multi-period dynamic model, job characteristics also depend on the supply of workers for that occupation. It is assumed that η_j is fixed and given as a constraint to an individual worker.

4.2.2 Sorting Mechanism

There are mainly two factors, individual job preference function and task level play an important role in the labor market sorting mechanism. The interaction between these two factors can explain individual worker's sorting behavior on equilibrium occupational choice. Job preference function represents the supply side behavior of the labor market and task level of any job represents firm's demand side phenomenon. The equilibrium wage depends on the workers cognitive and noncognitive skill levels and the task level of any given occupation.

Suppose a representative worker i has two occupations to choose from. Denote the occupations as η_1 and η_2. I choose a two occupation model because of the simplicity. This model can be generalized for n occupational choice model. Define t_1 and t_2 are the task levels for occupation η_1 and η_2 respectively where $t_2 > t_1$. It is reasonable to assume that wages are directly proportional to the task levels. Thus wage in the second occupation (η_2) is higher compared to the first occupation (η_1) because the task level is higher in the second occupation.

To perform the task level t_1 and t_2, workers need the skill level z_{min} and $z^\star$ respectively. We assume that workers have a continuous skill distribution from z_{min} to z_{max} where $z^\star <$

z_{max}. Each worker from this skill distribution has a preference function over these two occupations. This preference function is a rank function through which individual worker ranks the occupation based on his/her skill level and job characteristics. We denote τ_1 when workers prefer first occupation and τ_2 for the second occupation. We have the following two possible cases to consider based on the ranges of values of z, in a two occupational model: (i) for $z < z^{\star}$: $\{\tau_1, \tau_2\}$ (ii) for $z \geq z^{\star}$: $\{\tau_1, \tau_2\}$.

A trivial case is when an individual worker's skill level is less than $z^{\star}$. Although the worker has two occupation to choose from, he/she has to choose the first occupation η_1 because the worker can not perform the task level of the second occupation η_2. In this case the worker's preference function has no role to play because the worker has no other option except to choose the first occupation. From an employer point of view, a firm would never hire someone who is not able to perform the given task required for the second occupation. This is possible only when employers have perfect signal on workers' skill levels.

Another possible outcome is when an individual worker's skill level is greater equal to than $z^{\star}$. In this case, a worker can choose either occupation because he/she is capable of performing both the task. Assume that a worker prefers the second occupation over the first one. This implies that either the worker likes the job characteristics of the second job or the wage compensation between the two occupations dominates the monetary value of disliking some of the job characteristics. We can only observe the outcome, as a result we don't know which of the above two cases is true for any individual worker.

Suppose an individual worker prefers the second job compared to the first one even if the second job pays a higher wage. I follow the basic framework of equalizing differences model developed by Rosen (1986) and I make necessary changes for this given set up to analyse this case. Define M as the compensating variation necessary for a worker to be indifferent between accepting the job η_1 or η_2. That is, implicitly define M by the following equation,

$$u(w_1|\tau_1, z_1) = u(w_2 + M|\tau_2, z_2) \tag{4.5}$$

where M compensates a worker's preference over the first job and makes the worker indifferent between two jobs. M measures the monetary compensation of second job η_2, since we implicitly assume that representative worker does not like the job characteristics of η_2. M can also be think off as the reservation price of job characteristics employers need to pay to make the worker indifferent between accepting two jobs η_1 and η_2.

Denote ΔW is the wage differential between the two occupations and ΔW is always positive since w_2 is higher than w_1. Note that ΔW is fixed for all workers but M depends on the personal taste which varies from person to person, depending on their own circumstances and inherent preferences. For example, if someone strongly dislikes some of the job characteristics of the second job η_2, his/her M is higher compared to the person who dislikes the job characteristics of the second job less. However, some workers may like the job characteristics of η_2 compared to η_1 or be indifferent, in that case M takes the value zero.

I denote the probability density function of M across the members of labor force as $f(M)$ and the cumulative distribution function of M as $F(M)$ and normalize the total labor force to 1. Again, denote the density function of worker's skill level z as $g(z)$ and the cumulative distribution function as $G(z)$. Then the supply of workers in the first occupation (η_1) is given by:

$$N_1 = \int_0^{z^\star} g(z)dz + \int_{z^\star}^{1} \int_{\Delta W}^{1} f(M)g(z)dMdz \tag{4.6}$$

The first part of the above equation, $\int_0^{z^\star} g(z)dz$, represents those workers who do not have the skills to perform the task in the second occupation, causing them to choose the first occupation. The second part shows that among those workers who are capable of performing the task in both the jobs η_1 and η_2, they choose the first job η_1 because their reservation compensating monetary variation M is higher than the wage differential between the first and second occupation. The supply of workers in second occupation (η_2) is given by:

$$
\begin{aligned}
N_2 &= \int\limits_{z^\star}^{1} \left(1 - \int\limits_{\Delta W}^{1} f(M)\right) g(z) dM dz \\
&= \int\limits_{z^\star}^{1} \int\limits_{0}^{\Delta W} f(M) g(z) dM dz
\end{aligned} \tag{4.7}
$$

The above equation represents the remaining fraction of workers in the second occupation. These workers' reservation compensating monetary variation Ms are lower than the wage differential ΔW. The difference between this set up with Rosen's (1986) equalizing differences model is that the proposed model adds workers' skill distribution to the workers' optimal choice decision. In the long run equilibrium, the number of workers in η_2 depends on the distribution of the cost of modifying job characteristics by firms. Assume that $f(M)$ and $g(z)$ are normal, then we have the following selection bias terms as the discrepancy between the conditional and unconditional expectation functions:

$$
E(z|\tau_1) = \mu_z - \sigma_z \left(\phi \left(\frac{z^\star - \mu_z}{\sigma_z} \right) / \Phi \left(\frac{z^\star - \mu_z}{\sigma_z} \right) \right) \tag{4.8}
$$

$$
E(M|\tau_1) = \mu_M - \sigma_M \left(\phi \left(\frac{\Delta W - \mu_M}{\sigma_M} \right) / \Phi \left(\frac{\Delta W - \mu_M}{\sigma_M} \right) \right) \tag{4.9}
$$

4.2.3 Implementation of the Sorting Model

To implement the model, workers' years of schooling is used as a proxy of the skill level such that when education level is greater than a threshold value $z^\star$, an individual worker has the option to choose either occupation. The implicit assumption is that workers skill levels and schooling are highly correlated. The choice of $z^\star$ is the most important empirical challenge to implement the proposed sorting model because there are one to one mappings between schooling and skills required for different tasks. This implies that some less educated workers may be in the skilled sector occupation and vice versa. However, as long as the percentage of these two groups of workers are significantly low, schooling can be used as a proxy of the skill level $z^\star$.

The simplest choice of $z^\star$ is the average education level of occupation τ_1. A better measure of proxy variable is the specific degree requirement for any given task. One of the advantages of using the average education level as a proxy of $z^\star$ is that we can use different values of schooling to check the labor market sorting behavior. Suppose $z_1^\star$ and $z_2^\star$ are the average education levels for the first and second occupation respectively. One can use different values of $z^\star \in (z_1^\star, z_2^\star)$ for the purpose of robustness check. If the qualitative results of sorting behavior hold for different values of $z^\star$, then there must exist strong labor market sorting behavior based on noncognitive skills.

M is not observable for any individual. To estimate M, we need to construct a counterfactual wage for each worker. Suppose an individual worker chooses occupation τ_1. Then the counterfactual wage is defined as what would have been the wage of that worker if he/she chooses occupation τ_2. The counterfactual wage of an individual worker in occupation τ_1 is the wage of another worker who has similar observable characteristics in the occupation τ_2. The observable characteristics are schooling, experience, race and gender.

To estimate the counterfactual wage, suppose we consider four different education levels such as high school graduate, some college, college graduate and masters and above, and forty years of experience giving us 640 different groups of workers[1]. The average of each group of workers in τ_2 is the counterfactual wage of the same group of workers in τ_1. One can also use more robust method to construct the counterfactual wage as shown by DiNardo, Fortin and Lemieux (1996), Machodo and Mata (2005) and Firpo, Fortin and Lemieux (2011), Ghosh (2014).

[1] The combination of four different education levels and forty years of experience implies 160 groups of workers. We can further separate out the groups in terms of their race and gender. As a result we have total $160 \times 2 \times 2 = 640$ different groups of workers.

Suppose p_1 and p_2 to be the probability of choosing the first and second occupation, then one can use the following multinominal logit model specification:

$$log\left(\frac{p_1}{p_2}\right) = \alpha_0 + x_1\beta_1 + x_2\beta_2 + \lambda_z(z) + \lambda_M(M) + \epsilon$$

where x_1 and x_2 are the set of noncognitive skills and control variables, respectively, and $\lambda_z(\cdot)$ and $\lambda_M(\cdot)$ are the inverse Mills ratios of z and M. The advantage of using multinominal logit model in this case is that if we have more than two occupations, the log odds ratio, $\left(\frac{p_1}{p_2}\right)$, does not depend on the choices of the other occupations, which follows from the independence of the disturbances (ϵ).

To summarize, previous studies by Rosen (1986), Kruger and Schkade (2008) and many others have ignored the Heckman sample selection bias corrected term $\lambda_z(\cdot)$ to explain the labor market sorting behavior. As shown, ignoring the workers skill distribution on occupational choice model leads to bias and inconsistent coefficients because of the sample selection specification error. This paper proposes a solution of the problem by using number of years of schooling as the proxy of the workers skill level. However, the empirical challenge to implement the model is to determine the threshold value of schooling which makes a representative worker not attempts to work in the more skilled sector occupation. This paper also proposes average education level of relatively low skilled occupation as a proxy of $z^\star$ and for robustness check, one can use different values of education level as $z^\star$.

4.3 Data

Two data sources are used in this paper, O*NET (Occupational Information Network) and CPS (Current Population Survey). CPS contains income and all the necessary demographic variables of individual workers and O*NET contains workers' cognitive and noncognitive skills scales for 400 occupations, which exceeds the number of unique census occupation codes.

The 5 percent self-weighted 2010 sample CPS data consist of U.S.-born black and white men and women aged 18-65 with positive annual earnings and hours worked in the year preceding the census, and a nonzero sampling weight. The wage measure used is an hourly wage measure computed by dividing earnings by hours of work for workers not paid by the hour. For workers paid by the hour, I use a direct measure of the hourly wage rate. CPS weights are used throughout the empirical analysis. The regressors consist of years of schooling, potential experience and experience square, union coverage, marital status, race, gender, and statistical metropolitan area.

Like many researchers including Goos and Manning (2007), Goos, Manning and Salmons (2010), Autor and Acemoglu (2011), Firpo, Fortin and Lemieux (2011) who study the task content of jobs, I use the O*NET data to measure workers's cognitive and noncognitive skills. To keep categories manageable and self explanatory, out of 400 occupations in O*NET, we use broad occupational groupings in a total of seven. The seven classes are defined in CPS as: (1) professional and managerial and technical (2) clerical and sales (3) service (5) production (6) operators (7) transport. These seven categories map logically into the broad clusters identified in the conceptual framework.

Broadly speaking, managerial, professional and technical occupations are specialized in abstract, non-routine cognitive tasks. Clerical and sales occupations are specialized in routine cognitive tasks, production and operative occupations are specialized in routine manual tasks. O*NET task measures also make further distinction between non-routine cognitive analytical tasks and non-routine cognitive interpersonal and managerial tasks, routine cognitive and routine manual tasks. Logically, routine cognitive tasks are most prevalent in production and operative positions. Finally, non-routine manual tasks are those requiring flexibility and physical adaptability are most intensively used in production, operative and service positions.

To construct the variables, cognitive and noncognitive skills, I follow the three different measures of both cognitive and noncognitive skills from the O*NET data. Cognitive skills are composed of three broad category : (1) Decision making ability, (2) Data analyzing ability and (3) Resource management skills. Similarly noncognitive skills composed of (1) Interaction with others, (2) Interpersonal relationship and (3) Social skills. All these different types of cognitive and noncognitive skills are divided into many sub categories. Those sub categorical divisions are shown in the data appendix section.

The CPS and O*NET data sets are merged by using the three digit occupation code. For each occupation, the O*NET provides information on the 'importance' and 'level' of the required skill. Blinder (2007) arbitrarily assigns a Cobb-Douglas weight of two thirds to 'importance' and one third to 'level' to construct the required skill level for the task of any given occupation. In this study, I have used only the information under 'importance' because in the subcategories of the above mentioned six types of cognitive and noncognitive skills, almost two third cases the information on 'level' is missing. To obtain the six different measures of cognitive and noncognitive skills, I take the average of all those subcategories.

4.4 Labor Market Sorting Results

Table 1 represents the summary statistics of the O*NET and Current Population Survey (CPS) data. Both cognitive and noncognitive skills have been divided into three subcategories. The first column shows the mean of the six types of cognitive and noncognitive skills across all the occupations. Note that the highest average skill required for all occupations is social skill and the lowest skill is the resource management skill. The two most important skills are social skills and data analyzing ability across all the occupations. Two types of noncognitive skills, interaction with others and interpersonal relationships are equally important as cognitive skills, such as decision making ability. This table shows that irrespective of the types of occupations, noncognitive skills are equally important as cognitive skills to perform any given task.

The bottom half of table 1 shows the summary statistics of the demographic characteristics and the human capital variables. The sample consists of around half female workers, 12 percent black, 62 percent married and 76 percent urban workers. These numbers are fairly representative of the U.S. labor force. The average schooling is around 13 years with a standard deviation of 2.76 years. The last row represents the potential experience of the U.S. labor force. Potential experience may not reflect the actual experience since the CPS data does not track when a workers goes in and out of the labor force for a short period of time.

For male workers, potential experience has been calculated by subtracting 6 and the years of schooling from the worker's age, which is why the maximum potential experience is 59 years. It is a reasonable assumption that the male workers do not go out of the labor force too often. However this assumption is not valid for female workers because female workers may go out of the labor market multiple times for child birth. Buchnisky (1998) shows that ignoring that fact leads to potential measurement errors so I use his proposed method to estimate the female work experience by taking into account how many children any female worker have. If the number of children is zero then Buchnisky's (1998) method boils down to the method used for male workers' potential experience.

Table 2 shows the summary statistics of the O*NET and CPS data by seven different occupations. These occupations are defined as in the CPS. Each column represents the average cognitive and noncognitive skills of the workers of that specific occupation. The numbers in the parenthesis are the standard deviations. The lower panel shows that the mean and standard deviation of the demographic characteristics, human capital variables, and log hourly wage of the workers by occupation.

Apart from the professional, managerial and technical occupation, workers who are in the clerical and sales occupations need more cognitive skills compared to the occupations service, production, operators and Transport services. We note that clerical and sales workers also have a higher level of average education compared to the workers in the occupations service, production, operators and Transport services. Production workers need similar level of cognitive skills and lower level of noncognitive skills. However, production workers' average wage is higher compared to the clerical and sales workers'. As shown, 63.12 percent female workers are in the clerical and sales occupations, whereas 90.33 percent male workers are in the production occupation. These suggest that female workers prefers to work in the clerical and sales occupation compared to the production sector knowing that on an average yearly production workers earn around $\$4,500$ more.

By comparing the service sector with the operators and transport services, we see that the service sector needs more noncognitive skills compared to the operators and transport services. These workers also have higher average levels of education. However, the average of the hourly wage gap between the operator and transport sector with the service sector is around 2.5 and 3.25 dollars per hour. The percentage of the female workers in the service sector is around 60.71 percent whereas in the operators and transport services are 30.49 percent and 11.39 percent respectively. Again, on an average female workers prefer to work in the service sector more than operators and transport services, knowing still that they can earn more in operators and transport services.

From the above two comparisons, between clerical and production and service and operators and transport services, it is clear that female workers prefer the occupation where noncognitive skills are more important compared to the cognitive skills such as clerical and sales, and service sector. However, this may not necessarily be true for male workers who prefer to work in the cognitive skill intensive occupations because the production workers have less schooling compared to the clerical and sales workers. The is also true for the comparison between service and, operators and transport service workers. We don't know on average whether the male workers who are in the production, operators and transport service can perform the task level required for clerical and sales, and service sector or male workers in general prefer less noncognitive intensive skilled occupations.

As shown that the pattern of gender based labor market sorting does not hold for different races. In the sample, the percentage of black workers is around 12 percent. However, we note that only in two occupations professional, managerial and technical, and production the percentage of black workers are lower than the average. For the rest of the four occupations clerical and sales, service, operators and transport, the percentage is much higher than the average. Note that professional, managerial and technical, and production are the top two occupations in terms of the average hourly wage rate. The occupational choice of the black workers plays an important role on why the racial wage gap is not falling over time unlike the gender wage gap.

Table 3 reports the estimates log odd ratios of the multinominal logit models for the five occupations, clerical and sales, service, production, operators and transport, with respect to the baseline reference occupation professional, managerial and technical. The upper panel shows the results when we ignore any threshold level of education for the skilled sector occupation. This is the approach followed by the previous studies in the literature. As shown, these results are biased and inconsistent because of the sample selection error. The other half of table 3 shows the log odd ratios for high school graduate and college graduate as the threshold for professional, managerial and technical occupation.

The independent variables are three types of measures of noncognitive skills in all the labor marketing sorting models as shown in Table 3 to Table 6. These independent variables are standardized to mean 0 and standard deviation 1 across all the occupations. We also include controls for years of schooling, potential experience and experience square, marital status, race, and statistical metropolitan area in all the estimated models. The rationale for including these control variables is that they may be related with the worker's productivity and sorting based on worker's noncognitive skills, which is predicted to take place among workers who are equally productive.

The coefficient of interaction with others on clerical and sales occupation is 0.2462 as shown in Table 3 implies that for one standard deviation increase of the noncognitive skill interaction with others, the odd ratio to choose the clerical and sales occupation with respect to the professional, managerial and technical occupation increases by 0.2462%. This implies that as long as the odd ratio is less than 1, for one standard deviation increase in any particular type of noncognitive skills, workers are likely to choose the professional, managerial and technical occupation as opposed to the other occupations.

The marginal effect of the odds ratio for interpersonal relationship skill is greater than 1 for the occupations clerical and sales, service, operators and transport services except the occupation operators. Again, the marginal effects of social skills on clerical and sales and all three types of noncognitive skills on the service sector occupation are greater than 1 and varies from 1.19 to 4.5 for the specification where high school graduation as threshold for skilled sector occupation and from 1.18 to 4.39 for no threshold education level.

These results suggest that for one standard deviation increase in different types of noncognitive skills such as interpersonal relationship and social skill, workers prefer to choose clerical and sales and service sector occupation compared to the professional, managerial and technical occupation. These results hold for both the specification either $z^{\star} = 12$ or 0. This phenomenon is known as labor market sorting because workers choose their occupation based on their preferences over job characteristics and their noncognitive skill levels.

Table 4 and table 5 show the marginal effects of the three different types of noncognitive skills on the log odd ratios for the five occupations by gender and race, respectively. The sorting behaviors based on the noncognitive skills for the subgroups, male, female, white and black, are very similar to the overall pattern as shown in Table 3 for both the specifications. The marginal effects of noncognitive skills on the clerical and sales, and service sectors occupations are in general greater than one by gender and race.

The difference between the coefficients of similar subgroup of workers for the different specifications are both positive and negative as shown in Table 4 and Table 5. Some of those differences are statistically significant. This suggests that ignoring any threshold level of education cause biases in both the directions. By summarizing the results from Table 3 to Table 5, we conclude that for marginal changes in noncognitive skills, workers prefer the clerical and sales, and service occupations compared to the professional, managerial and technical occupation.

4.5 Conclusion

This paper shows a positive and statistically significant relationship between noncognitive skills and workers' sorting behavior in the U.S. labor market. In this study the level of workers' cognitive and noncognitive skills are exogenous by implicitly assuming that the stock of different noncognitive skills marginally changes, compared to the initial level because of on the job training. Although we control for total years of experience, ideally we need to control for the experience of how long the worker is employed in the current job. The incremental changes in skills due to on the job training bias the estimates in the upward direction.

To avoid the upward bias problem, we report the odd ratios of the probabilities to choose different occupations with respect to the professional, managerial and technical occupation rather than showing the actual parameter estimate for each occupation. As long as the biases are in the same direction given that an individual gains positive skills through on the job training in both the occupations, the marginal effects of the noncognitive skills on the probability odd ratio does not affect much. It is highly unlikely that in one occupation, a worker's noncognitive skill decreases during the job training, that possibility has been ruled out.

Although the stock of noncognitive skills is the outcome variable in many labor market studies, the objective of this study is not to explain what causes workers' different levels of noncognitive skills. A growing literature establishes that parental investment and early childhood environment have substantial impact on later life outcomes (see Knudsen et al. 2006, Cunha and Heckman 2008, Almond and Currie 2011). Recently, Heckman et al. (2013) show the mechanism through which early childhood experience affect adults' labor market outcomes.

Another concern is that workers treat the job characteristics as exogenously given to them. In a long run dynamic wage setting model, the job characteristics also depend on the workers preference function and the supply of workers in that job. Employers need to change the working environment and other aspects of jobs depending on the flow of workers and the monetary compensation. Employers can only change the monetary compensation rather than changing the job characteristics because it depends on the task level in the short run. A useful direction of future work is to examine the role of cognitive and noncognitive skills in the dynamic long run wage setting model.

There are two main contributions of this study in the literature. First, this paper proposes a new labor market sorting model by incorporating workers' cognitive and noncognitive skills on their job preference function. We have the famous sample selection specification error without considering the impact of workers' skill levels on their occupational choice decision. This paper proposes a solution to this problem by using education level as a proxy of workers' cognitive skills.

Second, the marginal effects of different types of noncognitive skills to choose occupations such as clerical and sales, and service with respect to the occupation professional, managerial and technical are almost always greater than 1. The relative magnitude of the coefficients varies a lot by race and gender. These results suggest that workers who have a higher level of social and interpersonal skills prefer the clerical and sales, and service occupations compared to the professional, managerial and sales given the existing wage differential occupation.

Appendix:

The sub categories of cognitive and noncognitive skills are defined in the Occupational Information Network website:

Decision Making Skill:

1. **Category Flexibility:** The ability to generate or use different sets of rules for combining or grouping things in different ways.

2. **Deductive Reasoning:** The ability to apply general rules to specific problems to produce answers that make sense.

3. **Flexibility of Closure:** The ability to identify or detect a known pattern (a figure, object, word, or sound) that is hidden in other distracting material.

4. **Fluency of Ideas:** The ability to come up with a number of ideas about a topic (the number of ideas is important, not their quality, correctness, or creativity).

5. **Inductive Reasoning:** The ability to combine pieces of information to form general rules or conclusions (includes finding a relationship among seemingly unrelated events).

6. **Information Ordering:** The ability to arrange things or actions in a certain order or pattern according to a specific rule or set of rules (e.g., patterns of numbers, letters, words, pictures, mathematical operations).

7. **Mathematical Reasoning:** The ability to choose the right mathematical methods or formulas to solve a problem.

8. **Memorization:** The ability to remember information such as words, numbers, pictures, and procedures.

9. **Number Facility:** The ability to add, subtract, multiply, or divide quickly and correctly.

10. **Oral Comprehension:** The ability to listen to and understand information and ideas presented through spoken words and sentences.

11. **Originality:** The ability to come up with unusual or clever ideas about a given topic or situation, or to develop creative ways to solve a problem.

12. **Perceptual Speed:** The ability to quickly and accurately compare similarities and differences among sets of letters, numbers, objects, pictures, or patterns. The things to be compared may be presented at the same time or one after the other. This ability also includes comparing a presented object with a remembered object.

13. **Problem Sensitivity:** The ability to tell when something is wrong or is likely to go wrong. It does not involve solving the problem, only recognizing there is a problem.

14. **Selective Attention:** The ability to concentrate on a task over a period of time without being distracted.

15. **Spatial Orientation:** The ability to know your location in relation to the environment or to know where other objects are in relation to you.

16. **Speed of Closure:** The ability to quickly make sense of, combine, and organize information into meaningful patterns.

17. **Time Sharing:** The ability to shift back and forth between two or more activities or sources of information (such as speech, sounds, touch, or other sources).

18. **Visualization:** The ability to imagine how something will look after it is moved around or when its parts are moved or rearranged.

19. **Written Comprehension:** The ability to read and understand information and ideas presented in writing.

20. **Written Expression:** The ability to communicate information and ideas in writing so others will understand.

Data Analyzing Skills:

1. **Analyzing Data or Information:** Identifying the underlying principles, reasons, or facts of information by breaking down information or data into separate parts.

2. **Developing Objectives and Strategies:** Establishing long-range objectives and specifying the strategies and actions to achieve them.

3. **Evaluating Information to Determine Compliance with Standards:** Using relevant information and individual judgment to determine whether events or processes comply with laws, regulations, or standards.

4. **Judging the Qualities of Things, Services, or People:** Assessing the value, importance, or quality of things or people.

5. **Making Decisions and Solving Problems:** Analyzing information and evaluating results to choose the best solution and solve problems.

6. **Organizing, Planning, and Prioritizing Work:** Developing specific goals and plans to prioritize, organize, and accomplish your work.

7. **Processing Information:** Compiling, coding, categorizing, calculating, tabulating, auditing, or verifying information or data.

8. **Scheduling Work and Activities:** Scheduling events, programs, and activities, as well as the work of others.

9. **Thinking Creatively:** Developing, designing, or creating new applications, ideas, relationships, systems, or products, including artistic contributions.

10. **Updating and Using Relevant Knowledge:** Keeping up-to-date technically and applying new knowledge to your job.

Resource Management Skill:

1. **Management of Financial Resources:** Determining how money will be spent to get the work done, and accounting for these expenditures.

2. **Management of Material Resources:** Obtaining and seeing to the appropriate use of equipment, facilities, and materials needed to do certain work.

3. **Management of Personnel Resources:** Motivating, developing, and directing people as they work, identifying the best people for the job.

4. **Time Management:** Managing one's own time and the time of others.

Interacting with Others:

1. **Assisting and Caring for Others:** Providing personal assistance, medical attention, emotional support, or other personal care to others such as coworkers, customers, or patients.

2. **Coaching and Developing Others:** Identifying the developmental needs of others and coaching, mentoring, or otherwise helping others to improve their knowledge or skills.

3. **Communicating with Persons Outside Organization:** Communicating with people outside the organization, representing the organization to customers, the public, government, and other external sources. This information can be exchanged in person, in writing, or by telephone or e-mail.

4. **Communicating with Supervisors, Peers, or Subordinates:** Providing information to supervisors, co-workers, and subordinates by telephone, in written form, e-mail, or in person.

5. **Coordinating the Work and Activities of Others:** Getting members of a group to work together to accomplish tasks.

6. **Developing and Building Teams:** Encouraging and building mutual trust, respect, and cooperation among team members.

7. **Establishing and Maintaining Interpersonal Relationships:** Developing constructive and cooperative working relationships with others, and maintaining them over time.

8. **Guiding, Directing, and Motivating Subordinates:** Providing guidance and direction to subordinates, including setting performance standards and monitoring performance.

9. **Interpreting the Meaning of Information for Others:** Translating or explaining what information means and how it can be used.

10. **Monitoring and Controlling Resources:** Monitoring and controlling resources and overseeing the spending of money.

11. **Performing Administrative Activities:** Performing day-to-day administrative tasks such as maintaining information files and processing paperwork.

12. **Performing for or Working Directly with the Public:** Performing for people or dealing directly with the public. This includes serving customers in restaurants and stores, and receiving clients or guests.

13. **Provide Consultation and Advice to Others:** Providing guidance and expert advice to management or other groups on technical, systems-, or process-related topics.

14. **Resolving Conflicts and Negotiating with Others:** Handling complaints, settling disputes, and resolving grievances and conflicts, or otherwise negotiating with others.

15. **Selling or Influencing Others:** Convincing others to buy merchandise/goods or to otherwise change their minds or actions.

16. **Staffing Organizational Units:** Recruiting, interviewing, selecting, hiring, and promoting employees in an organization.

17. **Training and Teaching Others:** Identifying the educational needs of others, developing formal educational or training programs or classes, and teaching or instructing others.

Interpersonal Relationship:

1. **Contact With Others:** How much does this job require the worker to be in contact with others (face-to-face, by telephone, or otherwise) in order to perform it?

2. **Coordinate or Lead Others:** How important is it to coordinate or lead others in accomplishing work activities in this job?

3. **Deal With External Customers:** How important is it to work with external customers or the public in this job?

4. **Deal With Physically Aggressive People:** How frequently does this job require the worker to deal with physical aggression of violent individuals?

5. **Deal With Unpleasant or Angry People:** How frequently does the worker have to deal with unpleasant, angry, or discourteous individuals as part of the job requirements?

6. **Electronic Mail:** How often do you use electronic mail in this job?

7. **Face-to-Face Discussions:** How often do you have to have face-to-face discussions with individuals or teams in this job?

8. **Frequency of Conflict Situations:** How often are there conflict situations the employee has to face in this job?

9. **Letters and Memos:** How often does the job require written letters and memos?

10. **Public Speaking:** How often do you have to perform public speaking in this job?
11. **Responsibility for Outcomes and Results:** How responsible is the worker for work outcomes and results of other workers?
12. **Responsible for Others' Health and Safety:** How much responsibility is there for the health and safety of others in this job?
13. **Telephone:** How often do you have telephone conversations in this job?
14. **Work With Work Group or Team:** How important is it to work with others in a group or team in this job?

Social Skill:

1. **Coordination:** Adjusting actions in relation to others' actions.
2. **Instructing:** Teaching others how to do something.
3. **Negotiation:** Bringing others together and trying to reconcile differences.
4. **Persuasion:** Persuading others to change their minds or behavior.
5. **Service Orientation:** Actively looking for ways to help people.
6. **Social Perceptiveness:** Being aware of others' reactions and understanding why they react as they do.

Table 4.1: Summary Statistics of ONET and CPS Data for All

Variable	Mean	Standard Deviation	Min	Max
Cognitive Skills				
Decision Making Ability	0.4821	0.0744	0.2638	0.7033
Data Analyzing Ability	0.5740	0.1121	0.2480	0.8250
Resource Management	0.3342	0.1028	0.1250	0.6475
Non-cognitive Skills				
Interaction With Others	0.4430	0.1062	0.1976	0.7841
Interpersonal Relationship	0.4662	0.0924	0.2064	0.7041
Social Skills	0.5890	0.1338	0.3050	0.9101
Demographics Characteristics				
Female	0.4909	0.4992	0	1
Black	0.1214	0.3265	0	1
Married	0.6251	0.4840	0	1
Non-urban	0.2446	0.4298	0	1
Human Capitals				
Education	13.8001	2.7637	0	21
Experience	20.8832	12.0756	0	59

Table 4.2: Summary Statistics of ONET and CPS Data for All by Occupation

Variable	Managerial and Technical	Clerical and Sales	Service	Production	Operators	Transport Services
Cognitive Skills						
Decision Making Ability	0.5454	0.4869	0.4370	0.4636	0.4157	0.4420
	(0.0506)	(0.0661)	(0.0726)	(0.0551)	(0.0545)	(0.0762)
Data Analyzing Ability	0.6743	0.5646	0.4971	0.5536	0.4915	0.5110
	(0.0762)	(0.0997)	(0.1173)	(0.0850)	(0.0861)	(0.1020)
Resource Management	0.4119	0.3140	0.2966	0.3163	0.2650	0.3085
	(0.1044)	(0.0829)	(0.1060)	(0.0811)	(0.0632)	(0.0918)
Non-cognitive Skills						
Interaction With Others	0.5291	0.4365	0.4570	0.3996	0.3454	0.3987
	(0.0924)	(0.0972)	(0.0830)	(0.0824)	(0.0702)	(0.0906)
Interpersonal Relationship	0.5295	0.4916	0.4692	0.4330	0.3524	0.4236
	(0.0737)	(0.0693)	(0.0947)	(0.0683)	(0.0752)	(0.0744)
Social Skills	0.6919	0.6200	0.6192	0.4463	0.4463	0.5175
	(0.1120)	(0.1240)	(0.1029)	(0.0752)	(0.0838)	(0.1088)
Demographics Characteristics						
Female	0.5434	0.6312	0.6071	0.0967	0.3049	0.1139
	(0.4981)	(0.4824)	(0.4884)	(0.2956)	(0.4604)	(0.3177)
Black	0.0944	0.1244	0.1760	0.0796	0.1509	0.1494
	(0.2924)	(0.3300)	(0.3808)	(0.2708)	(0.3580)	(0.3565)
Married	0.7119	0.5916	0.4986	0.6684	0.6072	0.5981
	(0.4528)	(0.4915)	(0.5000)	(0.4708)	(0.4884)	(0.4903)
Non-urban	0.2158	0.2317	0.2473	0.3001	0.3305	0.2896
	(0.4114)	(0.4219)	(0.4316)	(0.4583)	(0.4704)	(0.4536)
Human Capitals						
Education	15.7535	13.6212	12.4658	12.3276	11.7957	11.9673
	(2.3466)	(2.0137)	(2.5877)	(2.4961)	(2.7301)	(2.3098)
Experience	21.0138	20.4722	19.3240	22.0613	23.2960	22.3064
	(11.0807)	(12.4396)	(13.2020)	(11.5910)	(12.2218)	(12.3047)
Income						
Hourly Log Wage	3.2089	2.7621	2.4339	2.8868	2.6284	2.6653
	(0.7058)	(0.6661)	(0.6350)	(0.6067)	(0.5841)	(0.6175)
No of Obs	25,646	22,227	12,786	8,043	3,358	5,721

Table 4.3: Labor Market Sorting Results for All Workers : Multinominal Logit Estimation

No Education Level as Threshold for Skilled Sector Occupation

Noncognitive Skills	Clerical and Sales	Service	Production	Operators	Transport Services
Interaction With Others	0.2462	1.7831	0.6501	0.3080	0.6751
	(0.2272, 0.2671)	(1.6210, 1.9601)	(0.5881, 0.7180)	(0.2680, 0.3530)	(0.5941, 0.7680)
Interpersonal Relationship	4.3961	1.5120	2.6310	0.4840	2.2871
	(4.1141, 4.6980)	(1.4060, 1.6271)	(2.4061, 2.8772)	(0.4351, 0.5392)	(2.0501, 2.2551)
Social Skills	1.9360	1.1880	0.0882	0.7410	0.1460
	(1.8251, 2.0551)	(1.1091, 1.2730)	(0.0791, 0.0971)	(0.6581, 0.8340)	(0.1281, 0.1670)

High School Graduation as Threshold for Skilled Sector Occupation

Noncognitive Skills	Clerical and Sales	Service	Production	Operators	Transport Services
Interaction With Others	0.2251	1.6432	0.7601	0.2810	0.7391
	(0.2071, 0.2442)	(1.4892, 1.8131)	(0.6841, 0.8440)	(0.2423, 0.3281)	(0.6441, 0.8480)
Interpersonal Relationship	4.5011	1.5941	2.6920	0.5350	2.2511
	(4.2062, 4.8160)	(1.4790, 1.7182)	(2.4501, 2.9580)	(0.4772, 0.5991)	(2.0050, 2.5282)
Social Skills	1.9900	1.1960	0.0700	0.9352	0.1380
	(1.8721, 2.1140)	(1.1142, 1.2850)	(0.0620, 0.0781)	(0.8220, 1.0630)	(0.1201, 0.1590)

Table 4.4: Labor Market Sorting Results By Gender : Multinominal Logit Estimation

No Education Level as Threshold for Skilled Sector Occupation

	Clerical and Sales	Service	Production	Operators	Transport Services
Male					
Interaction With Others	0.1100	2.4640	0.6131	0.5440	0.6520
	$(0.0970, 0.1253)$	$(2.1281, 2.8530)$	$(0.5410, 0.6950)$	$(0.4571, 0.6480)$	$(0.5540, 0.7680)$
Interpersonal Relationship	5.9510	7.2030	4.9000	0.4921	5.7651
	$(5.3651, 6.6001)$	$(6.4191, 8.0832)$	$(4.3742, 5.4901)$	$(0.4230, 0.5392)$	$(5.0091, 6.6340)$
Social Skills	3.3381	0.4641	0.08001	0.6481	0.0951
	$(3.0281, 3.6803)$	$(0.5181, 0.5180)$	$(0.0712, 0.0913)$	$(0.5501, 0.7621)$	$(0.0800, 0.1120)$
Female					
Interaction With Others	0.3931	1.5550	0.9721	0.0351	1.5691
	$(0.3542, 0.4360)$	$(1.3630, 1.7740)$	$(0.7451, 1.2680)$	$(0.0271, 0.0462)$	$(1.1832, 2.0810)$
Interpersonal Relationship	2.9071	0.0365	0.4120	0.5561	0.2780
	$(2.6421, 3.1972)$	$(0.0326, 0.4092)$	$(0.3221, 0.5271)$	$(0.4692, 0.6593)$	$(0.2171, 0.3572)$
Social Skills	1.5880	2.4142	0.0851	2.5272	0.2142
	$(1.4591, 1.7282)$	$(2.1870, 2.6660)$	$(0.0650, 0.1102)$	$(2.0301, 3.1442)$	$(0.1672, 0.2752)$

High School Graduation as Threshold for Skilled Sector Occupation

	Clerical and Sales	Service	Production	Operators	Transport Services
Male					
Interaction With Others	0.0990	2.0822	0.6562	0.4752	0.6600
	$(0.0871, 0.1132)$	$(1.7881, 2.4241)$	$(0.5751, 0.7470)$	$(0.3941, 0.5732)$	$(0.5541, 0.7860)$
Interpersonal Relationship	5.9551	7.8131	4.9343	0.5571	5.8371
	$(5.3570, 6.6200)$	$(6.9340, 8.8041)$	$(4.3832, 5.5542)$	$(0.4760, 0.6531)$	$(5.0290, 6.7753)$
Social Skills	3.4830	0.4751	0.0732	0.6481	0.0093
	$(3.1511, 3.8512)$	$(0.4232, 0.5332)$	$(0.0641, 0.0842)$	$(0.5501, 0.7621)$	$(0.078, 0.1120)$
Female					
Interaction With Others	0.3721	1.5561	1.5972	0.0270	1.6600
	$(0.3350, 0.4140)$	$(1.3582, 1.7821)$	$(1.1920, 2.1402)$	$(0.0200, 0.0371)$	$(1.2331, 2.2332)$
Interpersonal Relationship	3.0271	0.3811	0.4420	0.5901	0.2881
	$(2.7472, 3.3361)$	$(0.3401, 0.4280)$	$(0.3311, 0.5900)$	$(0.4902, 0.7090)$	$(0.2220, 0.3731)$
Social Skills	1.5992	2.3900	0.0381	3.3271	0.2010
	$(1.4671, 1.7420)$	$(2.1583, 2.6462)$	$(0.0282, 0.0520)$	$(2.5850, 4.2832)$	$(0.1551, 0.2620)$

Table 4.5: Labor Market Sorting Results for By Race : Multinominal Logit Estimation

No Education Level as Threshold for Skilled Sector Occupation

	Clerical and Sales	Service	Production	Operators	Transport Services
White					
Interaction With Others	0.2260	1.8030	0.6632	0.3411	0.6021
	(0.2081, 0.2460)	(1.6271, 1.9972)	(0.5960, 0.7371)	(0.2490, 0.3950)	(0.5241, 0.6920)
Interpersonal Relationship	4.5711	1.5932	2.6800	0.4531	2.6170
	(4.2581, 4.9060)	(1.4721, 1.7240)	(2.4381, 2.9460)	(0.4031, 0.5090)	(2.3220, 2.9501)
Social Skills	2.0441	1.1682	0.0901	0.8151	0.1420
	(1.9192, 2.1771)	(1.0851, 1.2580)	(0.0801, 0.1000)	(0.7172, 0.9261)	(0.1230, 0.1642)
Black					
Interaction With Others	0.4570	2.0771	0.5230	0.1521	1.2451
	(0.3640, 0.5750)	(1.5931, 2.7091)	(0.3821, 0.7170)	(0.1040, 0.2241)	(0.8810, 1.7580)
Interpersonal Relationship	3.5810	1.2762	2.9141	0.6741	1.3032
	(2.9421, 4.3591)	(1.0391, 1.5670)	(2.2030, 3.8661)	(0.5081, 0.8940)	(0.9800, 1.7330)
Social Skills	1.3230	1.1190	0.0560	0.4461	0.1130
	(1.1032, 1.5882)	(0.9142, 1.3690)	(0.0400, 0.0790)	(0.3251, 0.6132)	(0.0821, 0.1540)

High School Graduation as Threshold for Skilled Sector Occupation

	Clerical and Sales	Service	Production	Operators	Transport Services
White					
Interaction With Others	0.2060	1.6552	0.7703	0.3141	0.6532
	(0.1891, 0.2241)	(1.4890, 1.8393)	(0.6892, 0.8610)	(0.2672, 0.3701)	(0.5611, 0.7592)
Interpersonal Relationship	4.6941	1.6940	2.7340	0.4952	2.5882
	(4.3670, 5.0451)	(1.5632, 1.8371)	(2.4751, 3.0210)	(0.4370, 0.5611)	(2.2781, 2.9410)
Social Skills	2.1050	1.1671	0.0721	1.0440	0.1323
	(1.9742, 2.2461)	(1.0812, 1.2600)	(0.0640, 0.0810)	(0.9082, 1.2002)	(0.1130, 0.1552)
Black					
Interaction With Others	0.4250	1.9201	0.6641	0.1381	1.3041
	(0.3371, 0.5362)	(1.4620, 2.5201)	(0.4782, 0.9221)	(0.0912, 0.2090)	(0.0912, 1.8690)
Interpersonal Relationship	3.5892	1.3080	3.1001	0.7381	1.3492
	(2.9380, 4.3842)	(1.0601, 1.6132)	(2.3072, 4.1662)	(0.5510, 0.9890)	(1.0070, 1.8093)
Social Skills	1.3370	1.1762	0.0410	0.5460	0.1131
	(1.1092, 1.6120)	(0.9540, 1.4492)	(0.0281, 0.0592)	(0.3892, 0.7661)	(0.0822, 0.1580)

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