Decomposing Wage Distributions Using Reweighing and Recentered Influence Function Regressions: A New Look at Labor Market Institutions and the Polarization of Male Earnings

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Related Papers


Motivation
The Polarization of Income

- Recently there has been a renewed interest for changes in wage inequality.

- These changes have been characterized as the “polarization” of the U.S. labor market into high-wage and low-wage jobs at the expense of middle-skill jobs (Autor, Katz and Kearney, 2006).

- These changes have also been called the “war on the middle-class” in the popular press.

- The stagnation of the average worker’ wages is in sharp contrast with the extremely high CEO’s pay which have made the headlines.
Motivation
The Polarization of Income
Motivation
The Polarization of Income

- Using Current Population Survey data, the recent changes in men’s wages look like this
Motivation
The Polarization of Income

- or like this

United States -- Men

- Log Wages in 2005 dollars
- Density

1988-90
2003-05
Motivation
Explanations for Increasing Wage Inequality

- To the extent that different explanations for these changes may provoke different policy responses, it is important to better understand the explanations or the sources of these changes.

- The consensus explanation of the early 1990s was that of skill-biased technological change (SBTC) (Krueger 1993; Bound, Berman, and Griliches 1994); but it is being challenged by recent trends and cross-country comparisons.

- The alternative explanation of international trade and globalization, has been found to play a relatively minor role [Feenstra and Hanson (2003) offer an explanation].
Motivation
A Role for the Labor Market Institutions?

- DiNardo, Fortin and Lemieux (1996), Lee (1999), DiNardo and Card (2002) have argued for a substantial role played by labor market institutions in increasing wage inequality.

- It is now generally accepted, even by proponents of the SBTC (Autor, Katz and Kearney, 2005), that changes in minimum wages explain a large portion of the increase in lower tail inequality, especially for women.

- For men, the decline of unionization remains a potentially attractive explanation for the “declining middle”.
Motivation
The Role of Other Factors

- For men, there is a consensus that growth in the upper tail of the wage distribution is associated with higher returns to education, especially post-graduate education (Lemieux, 2006)

- The goal of the paper will be to assess the role of various factors
  - Unionization
  - Education
  - Occupations (including high-wage occupations)
  - Industry (including high-tech sectors)
  - Other factors (including experience, non-white) on the changes in male wage inequality between 1988-90 and 2003-05 at various quantiles of the wage distribution
Motivation
Wage Structure or Composition Effects?

- Yet different factors have different impacts at different points of the wage distribution.

- Moreover, some factors are thought to have an impact through the “wage structure” or “price effects”, e.g. increasing returns to education.

- While other factors are thought to have an impact through “composition effects” or “quantity effects”, e.g. decline in union density.
Motivation
What explains what happens where?

- There exists no methodology that permits the decomposition of changes in wages at each quantile of the distribution into “composition” and “wage structure” effects, as in the Oaxaca-Blinder decomposition, for each explanatory variable.

- The DFL reweighing procedure can be used to divide an overall change into a composition and a wage structure effect, but not into components attributable to each explanatory variable.

- Main contribution of the paper is to show how our UQR regressions can be used to perform such a decomposition at different quantiles of the wage distribution.
Outline of the presentation

1. Methodological Issues:
   a. Beyond Oaxaca-Blinder
   b. Some Notation
   c. Step 1: Reweighing
   d. Step 2: RIF-regressions
   e. The Case of the Mean
   f. The Case of the Median

   a. Data
   b. Unconditional Quantile Regression Estimates
   c. Decomposition Results

3. Conclusion
Methodological Issues
Beyond Oaxaca-Blinder

- Oaxaca-Blinder decompositions are a popular tool of policy analysis.

- It assumes two groups, $T=0,1$, and a simple linear model, for $T=0$, $Y_{0i}=X_i\beta_0+\epsilon_i$ and for $T=1$, $Y_{1i}=X_i\beta_1+\epsilon_i$

- The overall average wage gap can be written as
  \[
  E(Y_1|T=1) - E(Y_0|T=0) = E(X|T=1)\beta_1 - E(X|T=0)\beta_0 \\
  = E(X|T=1)[\beta_1 - \beta_0] + [E(X|T=1) - E(X|T=0)]\beta_0
  \]
  or
  \[
  \Delta_o = \Delta_s + \Delta_x
  \]
  overall gap  wage structure effect + composition effect

- These effects can then subdivided into the contribution of each of the explanatory variable or a subset thereof.
Methodological Issues
Beyond Oaxaca-Blinder

- The Oaxaca-Blinder has its shortcomings.
- If the linear model is misspecified, this leads to misleading classification into wage structure or composition effects (Barsky et al. 2002).
- The focus only on the mean is limited to address complex changes in wage distributions (e.g. glass ceiling effects).
- There has been increasing interest in looking at what happens at different quantiles of the wage distribution.
Methodological Issues
Beyond Oaxaca-Blinder

- For example, Autor, Katz and Kearney, 2005 use the Machado-Mata methodology of numerically integrating conditional quantile regressions to reassess current explanations for rising wage inequality.

- An important disadvantage of the Machado-Mata methodology is that, unlike the classic Oaxaca-Blinder decomposition, it cannot be used to separate the composition effects into the contribution of each variable.

- It is also computationally intensive simulation method.
Methodological Issues
Beyond Oaxaca-Blinder

- We generalize the Oaxaca-Blinder method of decomposing wage differentials into wage structure and composition effects in several important ways.

  1) We apply this type of decomposition to any distributional features (and not only the mean) such as quantiles, the variance of log wages or the Gini.
  2) We estimate directly the elements of the decomposition instead of first estimating a structural wage-setting model.
  3) We break down the wage structure and composition effects into the contribution of each explanatory variable.

- We implement this decomposition in two steps.
Methodological Issues
Beyond Oaxaca-Blinder

- In Step 1, we divide the overall wage gap into a wage structure effect and a composition effect using a reweighing method.
Methodological Issues
Beyond Oaxaca-Blinder

In Step 2, we break down these terms—overall, composition and wage structure effects—into the contribution of the explanatory variables using the RIF-OLS regression.
In DFL, we used reweighing to construct counterfactual wage distributions; here, we appeal to the treatment effect literature to clarify the assumptions required for identification.

Using the notation of the treatment effects (potential outcomes) literature, where $T_i = 1$ if individual $i$ is observed in group 1 and $T_i = 0$, if in group 1.

Let $Y_{1,i}$ be the wage that worker $i$ would be paid in group 1 and $Y_{0,i}$ be the wage that would be paid in group 0.

Wage determination depends on $X$ and on some unobserved components $\epsilon \in \mathbb{R}^m$, through $Y_{1,i} = g_1(X_i, \epsilon_i)$ and $Y_{0,i} = g_0(X_i, \epsilon_i)$, where the $g_T(\cdot, \cdot)$ are some unknown wage structures.
Methodological Issues
Some Notation

- To simplify notation, let $Z_{1,i} = [Y_{1,i}, X_i]'$, $Z_{0,i} = [Y_{0,i}, X_i]'$, $Z_i = [Y_i, X_i]'$

- Denote the corresponding distribution

$$Z_1|T = 1 \sim^d F_1, \hspace{1cm} Z_0|T = 0 \sim^d F_0,$$

and

$$Z_0|T = 1 \sim^d F_{C},$$

be the counterfactual distribution that would have prevailed with the wage structure of group 0 but with individuals with observed and unobserved characteristics as of group 1, that is, the with distribution of $(X, \varepsilon)|T = 1.$
Methodological Issues
Step 1: Reweighing

- Let $\nu_1$, $\nu_0$ and $\nu_C$ be some functional of those distributions (variance, median, quantile, Gini, etc.)

- We write the difference in the $\nu$s between the two groups the $\nu$-overall wage gap, which is basically the difference in wages measured in terms of:

$$\Delta^{\nu}_0 = \nu_1 - \nu_0$$
Methodological Issues
Step 1: Reweighing

- The two key assumptions that we need to impose are
  - 1) that the error terms in the wage equation are ignorable, that is, conditional on X the distributions of the $\varepsilon$ are the same across groups;
  - 2) there is overlapping or common support of the observable characteristics, that is, no one value of a characteristic can perfectly predict belonging to one group.
Methodological Issues
Step 1: Reweighing

- Under these assumptions, we can decompose $\Delta\nu_0$ in two parts:
  \[
  \Delta\nu_0 = [\nu_1 - \nu_C] - [\nu_C - \nu_0] = \Delta\nu_S + \Delta\nu_X
  \]

- The first term $\Delta\nu_S$ represents the effect of changes in the “wage structure”. It corresponds to the effect on $\nu$ of a change from $g_0(\cdot, \cdot)$ to $g_1(\cdot, \cdot)$ keeping the distribution $(X, \varepsilon)|T = 1$.

- The second term $\Delta\nu_X$ is the composition effect and corresponds to changes in the distribution of $(X, \cdot)$, keeping the “wage structure” $g_0(\cdot, \cdot)$. 
Methodological Issues
Step 1: Reweighing

- We show that the distributions \( F_1, F_0 \) and \( F_C \) can be estimated non-parametrically using the weights

\[
\omega_1(T) = \frac{T}{p}, \quad \omega_0(T) = \frac{(1-T)}{(1-p)}
\]

\[
\text{and} \quad \omega_c(x,T) = \frac{p(x) \cdot (1-p) \cdot (1-T)}{1-p(x) \cdot p \cdot 1-p}
\]

where \( p(x) = \Pr[T = 1|X = x] \) is the proportion of people in the combined population of two groups that is in group 1, given that those people have \( X = x \), and \( p \) is that unconditional probability.
Methodological Issues
Step 1: Reweighing

- **Theorem 1 [Inverse Probability Weighing]:**
  Under Assumptions 1 and 2, for all \( x \) in \( X \):
  
  (i) \( F_t (z) = E[\omega_1(T) \cdot 1\{Y \leq y\} \cdot \prod_{l=1}^{r} 1\{X_l \leq x_l\}], \quad t = 0, 1 \)
  
  (ii) \( F_C (z) = E[\omega_c(x,T) \cdot 1\{Y \leq y\} \cdot \prod_{l=1}^{r} 1\{X_l \leq x_l\}] \),

- **Theorem 2 [Identification of Wage Structure and Composition Effects]:**
  Under Assumptions 1 and 2, for all \( x \) in \( X \):
  
  (i) \( \Delta^{\nu}_S, \Delta^{\nu}_X \) are identifiable from data on \( (Y, T,X) \);
  
  (ii) if \( g_1 (\cdot, \cdot) = g_0 (\cdot, \cdot) \) then \( \Delta^{\nu}_S = 0 \);
  
  (iii) if \( F_X|T=1 \sim F_X|T=0 \), then \( \Delta^{\nu}_X = 0 \)
Methodological Issues
Step 2: Application of the UQR methodology

- Here, we use a recently developed methodology (UQR) to obtain quantile regression estimates from the unconditional distribution of wages.
  - the general concept used (recentered influence function) applies to any distributional functional $\nu$, such as quantiles, the variance or the Gini.
  - these can be integrated up as easily as in the case of the mean.

- The RIF is simply a recentered IF, which is a well-known tool used in robust estimation and in computation of standard errors.

- Intuitively, the influence function (IF) represents to “contribution” of a given observation to the statistic (means, quantile, etc.) of interest.
Methodological Issues

Step 2: Application of the UQR methodology

- It is always the case that for any distributional functional \( \nu \):
  \[
  \nu = \int \text{RIF}(y; \nu) \cdot dF_Y(y) = \int E[\text{RIF}(Y; \nu | X = x)] \cdot dF_X(x)
  \]
  \[
  = E_X(E[\text{RIF}(Y; \nu | X = x)])
  \]
  where \( \text{RIF}(Y; \nu) \) is the recentered influence function.

- The \( \text{RIF}(Y; \nu) \), besides having an expected value equal to functional \( \nu \), corresponds to the leading term of a von Mises type expansion.

- The \( \text{RIF} \) regression, \( E[\text{RIF}(Y; q_\tau | X)] = X'\gamma_\tau \), is called the UQR in the case of quantiles and \( \gamma_\tau \) (called UQPE) is simply the regression parameter of \( \text{RIF}(Y; q_\tau) \) on \( X \).
Methodological Issues
Step 2: Application of the new UQR methodology

Then

\[ \Delta^{\nu}_O = E_X(E[RIF(Y_1;\nu_1|X,T=1)] - E_X(E[RIF(Y_0;\nu_0|X,T=0)]) \]

\[ \Delta^{\nu}_S = E_X(E[RIF(Y_1;\nu_1|X,T=1)] - E_X(E[RIF(Y_0;\nu_C|X,T=1)]) \]

\[ \Delta^{\nu}_X = E_X(E[RIF(Y_0;\nu_C|X,T=1)] - E_X(E[RIF(Y_0;\nu_0|X,T=0)]) \]
Methodological Issues
Step 2: Application of the new UQR methodology

- Then in the case where the conditional expectation is linear, letting $\gamma_v$ is the parameter of the RIF-regression $E[\text{RIF}(Y;\nu)|X] = X'\gamma_v$.

$$\Delta_{S}^\nu = E_X(X|T=1)\gamma_1 - E_X(X|T=1)\gamma_C$$
$$= E_X(X|T=1)[\gamma_1 - \gamma_C]$$

and

$$\Delta_{X}^\nu = E_X(X|T=1)\gamma_C - E_X(X|T=0)\gamma_0$$
$$= E_X(X|T=1)\gamma_C - E_X(X|T=0)\gamma_0 + E_X(X|T=1)\gamma_0 - E_X(X|T=1)\gamma_0$$
$$= [E_X(X|T=1) - E_X(X|T=0)]\gamma_0 + E_X(X|T=1)[\gamma_C - \gamma_0]$$

- As in the Oaxaca-Blinder, these effects can then subdivided into the contribution of each of the explanatory variable.
Methodological Issues:
The Case of the Mean

- Assume two groups, T=0,1 and a simplified model
  For T=0, $Y_{0i} = X_i \beta_0 + \varepsilon_i$ and for T=1, $Y_{1i} = X_i \beta_1 + \varepsilon_i$

- The overall average wage gap can be written as
  $E(Y_{1|T=1}) - E(Y_{0|T=0}) = E(X|T=1) \beta_1 - E(X|T=0) \beta_0$
  $= E(X|T=1) [\beta_1 - \beta_c] + [E(X|T=1)\beta_c - E(X|T=0)\beta_0]$
  or $\Delta \mu_o = \Delta \mu_s + \Delta \mu_x$
  overall gap wage structure effect + composition effect

  where $\beta_c$ is a counterfactual wage structure
Methodological Issues
The Case of the Mean

- We define the counterfactual wage structure $\beta_c$, such that 
  $E(Y_0|T=1,X)= X_i' \beta_c$

- That is, we propose to estimate $\beta_c$ by OLS (linear projection) on the 
  $T = 0$ sample reweighed to have the same distribution of $X$ as in 
  period $T = 1$.

- In practice, the reweighing uses an estimate of the “propensity-score” $p(x) = Pr[T = 1|X = x]$ the proportion of people in the 
  combined population of two groups that is in group 1, given that 
  those people have $X = x$. 
Methodological Issues
The Case of the Mean

- In the case of the mean, we have $\text{RIF}_\mu = Y_i$ since the influence function of the mean is $Y_i - \mu$.

- The RIF-regression (conditional expectation of the RIF) corresponds to the OLS regression because
  \[ E[\text{RIF}(Y;\mu|X)] = E(Y|X) \]

- Here the expected (over $X$) value of conditional mean is simply the unconditional mean by the Law of Iterated Expectations:
  \[ \mu = E(Y) = E_x [E(Y | X=x)] = E(X)\beta_{OLS} \]

- The usual OLS regression is both a model for conditional mean and the unconditional mean because fitted values average out to the unconditional mean.
Methodological Issues
The Case of the Median

- In the case of quantiles, because in general, $Q_\tau(Y) \neq E_X[Q_\tau(Y|X)]$, we cannot use conditional quantile regressions.

- So even if quantile regressions yield estimates of $Q_\tau(Y|X) = X'\alpha_\tau$, we would have
  \[ Q_\tau(Y) \neq E_X[Q_\tau(Y|X)] = E_X[X]\alpha_\tau \]

- That is, quantile regression coefficients cannot be used to decompose the corresponding unconditional quantile.

- By contrast, the method we propose here refers to the effects of changes in $X$ on unconditional quantiles of $Y$. 
Methodological Issues: The Case of the Median

- In the case of the quantile (median $\tau=0.5$), we have
  \[ RIF(Y_i; q_{\tau}) = q_{\tau} + [\tau - 1(Y_i \leq q_{\tau}) ]/f_y(q_{\tau}) \]
  \[ = [1(Y_i > q_{\tau}) ]/f_y(q_{\tau}) + q_{\tau} - (1 - \tau)/ f_y(q_{\tau}) \]
  \[ = c_{1,\tau} [1(Y_i > q_{\tau}) ] + c_{2,\tau} \]
  where $c_{1,\tau} = 1/f_y(q_{\tau})$ and $c_{2,\tau} = q_{\tau} - c_{1,\tau} (1 - \tau)$

- It follows that
  \[ E[RIF(Y ; q_{\tau}) | X] = c_{1,\tau} E [1(Y_i > q_{\tau}) | X] + c_{2,\tau} \]
  \[ = c_{1,\tau} Pr [Y_i > q_{\tau} | X] + c_{2,\tau} \]

- The scaling factor, $1/f_y(q_{\tau})$, translates this probability impact into a $Y$ impact since the relationship between $Y$ and probability is the inverse CDF and its slope is the inverse of the density ($1/f$)
Methodological Issues
The Case of the Median

Figure A: Relationship Between the Effect of X (t increase) on Unconditional Quantiles (UQPE) and Probabilities

\[ \tau = \text{Prob}(Y \le q_t), \]
\[ \tau' = \text{Prob}(h(X+t, \varepsilon) \le q_t) \]
\[ q_{t'} \text{ is such that } \tau = \text{Prob}(h(X+t, \varepsilon) \le q_{t'}) \]

\[ F(Y) = F(h(X, \varepsilon)) \]

\[ F(h(X+t, \varepsilon)) \]

\[ q_{t'} - q_t = m(\tau - \tau'), \]
where \( m \approx 1/f \), and \( f \) is the density

Cumulative probability

Outcome variable (Y)

This results in large sample size: 226,078 obs. in 1988-90, and 170,693 obs. in 2003-05

The dependent variable is log hourly wages.

Observations with allocated wages are deleted; top-coding applies to a small percentage and is left alone.

The specification is used for the UQR wage regressions includes covered by a union, non-white, non-married, 6 education classes, 9 experience classes, 17 occupations classes and 14 industry classes.
**Decomposition**

**Data: Table 1. Sample means**

<table>
<thead>
<tr>
<th></th>
<th>1988-90</th>
<th>2003-05</th>
<th>Δ</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log wages</td>
<td>2.179</td>
<td>2.237</td>
<td>0.058</td>
</tr>
<tr>
<td>Std of log wages</td>
<td>0.576</td>
<td>0.595</td>
<td>0.019</td>
</tr>
<tr>
<td>Union covered</td>
<td>0.223</td>
<td>0.152</td>
<td>-0.072</td>
</tr>
<tr>
<td>Non-white</td>
<td>0.127</td>
<td>0.133</td>
<td>0.006</td>
</tr>
<tr>
<td>Non-Married</td>
<td>0.386</td>
<td>0.408</td>
<td>0.022</td>
</tr>
<tr>
<td>Education</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Primary</td>
<td>0.060</td>
<td>0.046</td>
<td>-0.014</td>
</tr>
<tr>
<td>Some HS</td>
<td>0.121</td>
<td>0.082</td>
<td>-0.038</td>
</tr>
<tr>
<td>High School</td>
<td>0.379</td>
<td>0.308</td>
<td>-0.070</td>
</tr>
<tr>
<td>Some College</td>
<td>0.203</td>
<td>0.271</td>
<td>0.068</td>
</tr>
<tr>
<td>College</td>
<td>0.137</td>
<td>0.193</td>
<td>0.056</td>
</tr>
<tr>
<td>Post-grad</td>
<td>0.100</td>
<td>0.099</td>
<td>-0.001</td>
</tr>
<tr>
<td>Age</td>
<td>35.766</td>
<td>38.249</td>
<td>2.483</td>
</tr>
</tbody>
</table>
Decomposition
Unionization and the “Declining Middle”

- For men, a potentially attractive explanation for the “declining middle” phenomena remains the decline of unionization.
# Decomposition

## Data: Table 1. Sample means

<table>
<thead>
<tr>
<th>Occupations</th>
<th>1988-90</th>
<th>2003-05</th>
<th>Δ</th>
</tr>
</thead>
<tbody>
<tr>
<td>Upper Management</td>
<td>0.080</td>
<td>0.079</td>
<td>-0.001</td>
</tr>
<tr>
<td>Lower Management</td>
<td><strong>0.039</strong></td>
<td><strong>0.058</strong></td>
<td>0.019</td>
</tr>
<tr>
<td>Scientists</td>
<td><strong>0.074</strong></td>
<td><strong>0.085</strong></td>
<td>0.011</td>
</tr>
<tr>
<td>Social Support Occ</td>
<td><strong>0.052</strong></td>
<td><strong>0.064</strong></td>
<td>0.012</td>
</tr>
<tr>
<td>Lawyers &amp; Judges</td>
<td>0.006</td>
<td>0.006</td>
<td>0.001</td>
</tr>
<tr>
<td>Doctors &amp; Dentists</td>
<td>0.004</td>
<td>0.006</td>
<td>0.002</td>
</tr>
<tr>
<td>Health Treatment Occ</td>
<td>0.010</td>
<td>0.014</td>
<td>0.004</td>
</tr>
<tr>
<td>Clerical Occ</td>
<td>0.066</td>
<td>0.071</td>
<td>0.005</td>
</tr>
<tr>
<td>Sales Occ</td>
<td>0.084</td>
<td>0.090</td>
<td>0.006</td>
</tr>
<tr>
<td>Insurance Sales</td>
<td>0.004</td>
<td>0.003</td>
<td>-0.001</td>
</tr>
<tr>
<td>Real Estate Sales</td>
<td>0.003</td>
<td>0.002</td>
<td>0.000</td>
</tr>
<tr>
<td>Financial Sales</td>
<td>0.003</td>
<td>0.003</td>
<td>0.000</td>
</tr>
<tr>
<td>Service Occ</td>
<td><strong>0.108</strong></td>
<td><strong>0.133</strong></td>
<td>0.025</td>
</tr>
<tr>
<td>Primary Occ</td>
<td><strong>0.028</strong></td>
<td><strong>0.012</strong></td>
<td>-0.016</td>
</tr>
<tr>
<td>Construction &amp; Repair Oc</td>
<td>0.163</td>
<td>0.172</td>
<td>0.009</td>
</tr>
<tr>
<td>Production Occ</td>
<td><strong>0.144</strong></td>
<td><strong>0.100</strong></td>
<td>-0.044</td>
</tr>
<tr>
<td>Transportation Occ</td>
<td><strong>0.133</strong></td>
<td><strong>0.101</strong></td>
<td>-0.032</td>
</tr>
</tbody>
</table>
## Decomposition

**Data: Table 1. Sample means**

<table>
<thead>
<tr>
<th>Industries</th>
<th>1988-90</th>
<th>2003-05</th>
<th>Δ</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture, Mining</td>
<td>0.035</td>
<td>0.022</td>
<td>-0.013</td>
</tr>
<tr>
<td>Construction</td>
<td>0.096</td>
<td>0.115</td>
<td>0.019</td>
</tr>
<tr>
<td>Hi-Tech Manufac</td>
<td>0.101</td>
<td>0.075</td>
<td>-0.026</td>
</tr>
<tr>
<td>Low-Tech Manufac</td>
<td>0.139</td>
<td>0.104</td>
<td>-0.036</td>
</tr>
<tr>
<td>Wholesale Trade</td>
<td>0.051</td>
<td>0.045</td>
<td>-0.006</td>
</tr>
<tr>
<td>Retail Trade</td>
<td>0.106</td>
<td>0.116</td>
<td>0.010</td>
</tr>
<tr>
<td>Transportation &amp; Utilities</td>
<td>0.085</td>
<td>0.072</td>
<td>-0.013</td>
</tr>
<tr>
<td>Information except Hi-Tech</td>
<td>0.018</td>
<td>0.015</td>
<td>-0.002</td>
</tr>
<tr>
<td>Financial Activities</td>
<td>0.045</td>
<td>0.054</td>
<td>0.009</td>
</tr>
<tr>
<td>Hi-Tech Services</td>
<td>0.035</td>
<td>0.054</td>
<td>0.019</td>
</tr>
<tr>
<td>Business Services</td>
<td>0.069</td>
<td>0.057</td>
<td>-0.012</td>
</tr>
<tr>
<td>Education &amp; Health Services</td>
<td>0.097</td>
<td>0.105</td>
<td>0.008</td>
</tr>
<tr>
<td>Personal Services</td>
<td>0.103</td>
<td>0.115</td>
<td>0.012</td>
</tr>
<tr>
<td>Public Admin</td>
<td>0.058</td>
<td>0.052</td>
<td>-0.006</td>
</tr>
</tbody>
</table>
## Decomposition

**Data: Union coverage by industry**

<table>
<thead>
<tr>
<th>Industries</th>
<th>1988-90</th>
<th>2003-05</th>
<th>Δ</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture, Mining</td>
<td>0.094</td>
<td>0.060</td>
<td>-0.034</td>
</tr>
<tr>
<td>Construction</td>
<td>0.256</td>
<td>0.178</td>
<td>-0.078</td>
</tr>
<tr>
<td>Hi-Tech Manufac</td>
<td>0.273</td>
<td>0.149</td>
<td>-0.124</td>
</tr>
<tr>
<td>Low-Tech Manufac</td>
<td>0.277</td>
<td>0.156</td>
<td>-0.122</td>
</tr>
<tr>
<td>Wholesale Trade</td>
<td>0.102</td>
<td>0.071</td>
<td>-0.032</td>
</tr>
<tr>
<td>Retail Trade</td>
<td>0.103</td>
<td>0.070</td>
<td>-0.033</td>
</tr>
<tr>
<td>Transportation &amp; Utilities</td>
<td>0.454</td>
<td>0.353</td>
<td>-0.101</td>
</tr>
<tr>
<td>Information except Hi-Tech</td>
<td>0.178</td>
<td>0.123</td>
<td>-0.055</td>
</tr>
<tr>
<td>Financial Activities</td>
<td>0.054</td>
<td>0.041</td>
<td>-0.013</td>
</tr>
<tr>
<td>Hi-Tech Services</td>
<td>0.182</td>
<td>0.074</td>
<td>-0.108</td>
</tr>
<tr>
<td>Business Services</td>
<td>0.080</td>
<td>0.057</td>
<td>-0.023</td>
</tr>
<tr>
<td>Education &amp; Health Services</td>
<td>0.298</td>
<td>0.261</td>
<td>-0.037</td>
</tr>
<tr>
<td>Personal Services</td>
<td>0.055</td>
<td>0.049</td>
<td>-0.006</td>
</tr>
<tr>
<td>Public Admin</td>
<td>0.422</td>
<td>0.412</td>
<td>-0.010</td>
</tr>
</tbody>
</table>
Decomposition
Unconditional Quantile Regression Results

- RIF-OLS regressions are estimated at every 5th quantile
- Base group is composed of married white individuals with some college, and between 20 and 25 years of experience
- The occupations and industries are normalized so that they are neutral for the base group in 2003-05
- In all types of Oaxaca decompositions, part of the “unexplained” gap or the “wage structure effect” depends on the base group
- This problem is exacerbated here when there is a lack of support of the base group in some parts of the wage distribution
### Decomposition

**Unconditional Quantile Regression Results**

<table>
<thead>
<tr>
<th>Quantile</th>
<th>1988-90</th>
<th></th>
<th>2003-05</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>10</td>
<td>50</td>
<td>90</td>
<td>10</td>
</tr>
<tr>
<td>Union covered</td>
<td>0.154</td>
<td>0.394</td>
<td>-0.032</td>
<td>0.101</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.003)</td>
<td>(0.005)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Non-white</td>
<td>-0.069</td>
<td>-0.140</td>
<td>-0.079</td>
<td>-0.039</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.004)</td>
<td>(0.005)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Non-Married</td>
<td>-0.132</td>
<td>-0.120</td>
<td>-0.032</td>
<td>-0.094</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.003)</td>
<td>(0.004)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Primary</td>
<td>-0.376</td>
<td>-0.479</td>
<td>-0.230</td>
<td>-0.417</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.006)</td>
<td>(0.009)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>Some HS</td>
<td>-0.384</td>
<td>-0.257</td>
<td>-0.106</td>
<td>-0.419</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.005)</td>
<td>(0.007)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>High School</td>
<td>-0.049</td>
<td>-0.132</td>
<td>-0.110</td>
<td>-0.064</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.005)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>College</td>
<td>0.085</td>
<td>0.226</td>
<td>0.342</td>
<td>0.064</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.005)</td>
<td>(0.006)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Post-grad</td>
<td>0.031</td>
<td>0.292</td>
<td>0.712</td>
<td>0.028</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.006)</td>
<td>(0.008)</td>
<td>(0.006)</td>
</tr>
</tbody>
</table>
Decomposition
UQR Results: Union, Education, etc.
Decomposition
UQR Results: Sensitivity Analysis

- The impact of unionization on male log wages 1983-85
- Comparison with other estimates
  - OLS (---)
  - Conditional Quantile (—)

![Graphs showing the impact of unionization on log wages with OLS and Conditional Quantile estimates.]
Decomposition
UQR Results: Selected Occupations

Upper Management
Doctors & Dentists
Financial Sales
Scientists
Health Treatment Occ.
Production Occ.
Transportation Occ.
Service Occ.
Decomposition
UQR Results: Selected Industries
Decomposition Results

Total Effects: \( \Delta \nu_O = [\nu_I - \nu_C] - [\nu_C - \nu_0] = \Delta \nu_S + \Delta \nu_X \)
## Decomposition Results

### Total Effects

<table>
<thead>
<tr>
<th>Source</th>
<th>90-10</th>
<th>50-10</th>
<th>90-50</th>
</tr>
</thead>
<tbody>
<tr>
<td>Union</td>
<td>0.025</td>
<td>-0.015</td>
<td>0.040</td>
</tr>
<tr>
<td>Occupation</td>
<td>-0.009</td>
<td>0.004</td>
<td>-0.013</td>
</tr>
<tr>
<td>Industry</td>
<td>0.004</td>
<td>0.005</td>
<td>-0.001</td>
</tr>
<tr>
<td>Education</td>
<td>0.083</td>
<td>0.022</td>
<td>0.061</td>
</tr>
<tr>
<td>Other</td>
<td>-0.015</td>
<td>-0.009</td>
<td>-0.006</td>
</tr>
<tr>
<td>Residual</td>
<td>-0.030</td>
<td>-0.074</td>
<td>0.045</td>
</tr>
<tr>
<td>Total</td>
<td>0.059</td>
<td>-0.066</td>
<td>0.125</td>
</tr>
</tbody>
</table>
Decomposition Results:
Composition Effects:
\[ \Delta \nu_X = [E_x(X|T=1) - E_x(X|T=0)] \gamma_0 + E_x(X|T=1)[\gamma_C - \gamma_0] \]

<table>
<thead>
<tr>
<th>Quantile</th>
<th>Total</th>
<th>Explained</th>
<th>Spec. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-10</td>
<td>0.072</td>
<td>0.032</td>
<td>0.032</td>
</tr>
<tr>
<td>50-10</td>
<td>0.025</td>
<td>0.008</td>
<td>-0.007</td>
</tr>
<tr>
<td>90-50</td>
<td>0.047</td>
<td>0.015</td>
<td>0.015</td>
</tr>
</tbody>
</table>
Decomposition Results:
Composition Effects

<table>
<thead>
<tr>
<th></th>
<th>90-10</th>
<th>50-10</th>
<th>90-50</th>
</tr>
</thead>
<tbody>
<tr>
<td>Union</td>
<td>0.014</td>
<td>-0.018</td>
<td>0.031</td>
</tr>
<tr>
<td>Occupation</td>
<td>0.010</td>
<td>0.017</td>
<td>-0.007</td>
</tr>
<tr>
<td>Industry</td>
<td>0.016</td>
<td>0.009</td>
<td>0.007</td>
</tr>
<tr>
<td>Education</td>
<td>0.006</td>
<td>0.010</td>
<td>-0.005</td>
</tr>
<tr>
<td>Other</td>
<td>0.018</td>
<td>0.013</td>
<td>0.005</td>
</tr>
<tr>
<td>Spec. error</td>
<td>0.008</td>
<td>-0.007</td>
<td>0.015</td>
</tr>
<tr>
<td>Total</td>
<td>0.072</td>
<td>0.025</td>
<td>0.047</td>
</tr>
</tbody>
</table>
Decomposition Results

Wage Structure Effects: \( \Delta \nu_S = E_X(X|T=1)[\nu_1 - \nu_C] \)

<table>
<thead>
<tr>
<th>Wage Structure Effects</th>
<th>90-10</th>
<th>50-10</th>
<th>90-50</th>
</tr>
</thead>
<tbody>
<tr>
<td>Explained</td>
<td>0.025</td>
<td>-0.024</td>
<td>0.049</td>
</tr>
<tr>
<td>Residual</td>
<td>-0.038</td>
<td>-0.067</td>
<td>0.029</td>
</tr>
<tr>
<td>Total</td>
<td>-0.013</td>
<td>-0.091</td>
<td>0.078</td>
</tr>
</tbody>
</table>
Decomposition Results:
Wage Structure Effects

<table>
<thead>
<tr>
<th>Wage Structure Effects:</th>
<th>90-10</th>
<th>50-10</th>
<th>90-50</th>
</tr>
</thead>
<tbody>
<tr>
<td>Union</td>
<td>0.011</td>
<td>0.003</td>
<td>0.009</td>
</tr>
<tr>
<td>Occupation</td>
<td>-0.019</td>
<td>-0.013</td>
<td>-0.006</td>
</tr>
<tr>
<td>Industry</td>
<td>-0.012</td>
<td>-0.003</td>
<td>-0.008</td>
</tr>
<tr>
<td>Education</td>
<td>0.078</td>
<td>0.012</td>
<td>0.066</td>
</tr>
<tr>
<td>Other</td>
<td>-0.033</td>
<td>-0.022</td>
<td>-0.012</td>
</tr>
<tr>
<td>Residual</td>
<td>-0.038</td>
<td>-0.067</td>
<td>0.029</td>
</tr>
<tr>
<td>Total</td>
<td>-0.013</td>
<td>-0.091</td>
<td>0.078</td>
</tr>
</tbody>
</table>
Decomposition Results:
Summary

- Increases in top-end wage inequality are best accounted for by
  - Wage structure effects associated with education (post-graduate)
  - Composition effects associated with de-unionization

- Decreases in low-end wage inequality are best accounted for by
  - Wage structure effects associated with occupations and “other” factors
  - Composition effects associated with de-unionization

- Increases in total wage inequality are best accounted for by
  - Composition effects associated with other factors, industry, unionization, and occupation by order of importance.
Decomposition Results:
Discussion

- We show that de-unionization and changes in returns to education remain the dominant factors accounting for changes in wage inequality in the 1990s.

- We find that the role of occupation and industry are also found to play a role, but it is difficult to assign these changes to SBTC.

- Our results are suggestive that
  - Social norms may also be at play to explain changes in returns to occupations such as financial analysts, doctors and dentists, as argued by Piketty and Saez (2003).
Conclusion:

- In this paper,
  - we propose a new methodology to perform Oaxaca-Blinder type decomposition for any distributional measure (for which an influence function can be computed)
  - the methodology can also be used to analyze changes in Gini and other measures
  - we implement this methodology to study changes in male earnings inequality from 1988-90 to 2003-05
Appendix
Issues Associated with Choice of Base Group

- Base group are married, white individual with between 20 and 25 years of experience and indicated education level
Appendix
Minimum Wages and Wage Inequality

Figure 1. Kernel Density Estimates of Real Log Wages ($1979)

Source: Fortin and Lemieux, JEP (1997)
Appendix
Basic Concepts

- The influence function is a measure of the infinitesimal behavior of real-valued functionals \( \nu (F) \), where \( \nu : \mathcal{F}_\nu \rightarrow \mathbb{R} \) and \( \mathcal{F}_\nu \) is a class of distribution functions such that \( F \in \mathcal{F}_\nu \) if \( |\nu (F)| < +\infty \).

- Following Huber (1977), we say that \( \nu (\cdot) \) is Gâteaux differentiable at \( F \) if there is a real function \( a (\cdot) \) such that for all \( G \) in \( \mathcal{F}_\nu \):

\[
\lim_{t \downarrow 0} \frac{\nu (F_{t,G}) - \nu (F)}{t} = \frac{\partial \nu (F_{t,G})}{\partial t} \bigg|_{t=0} = \int a(y) \cdot d(G - F)(y) \tag{1}
\]

where \( 0 \leq t \leq 1 \) and where the mixing distribution \( F_{t,G} \)

\[
F_{t,G} = (1 - t) \cdot F + t \cdot G = t \cdot (G - F) + F \tag{2}
\]

is the probability distribution that is \( t \) away from \( F \) in the direction of the probability distribution \( G \).
Appendix
Basic Concepts

- The concept of influence function arises from the case in which \( G \) is replaced by \( \Delta_y \), the probability measure that put mass 1 at the value \( y \), in the mixture \( F_t \cdot G \). This yields \( F_t \cdot \Delta_y \), the distribution that adds a blip or a contaminant at the point \( y \),

\[
F_t \cdot \Delta_y \equiv (1 - t) \cdot F + t \cdot \Delta_y
\]

The influence function of the functional \( \nu \) at \( F \) for a given point \( y \) is defined as

\[
IF(y; \nu, F) \equiv \frac{\partial \nu \left( F_t \cdot \Delta_y \right)}{\partial t} \bigg|_{t=0} = \int a(y) \cdot d\Delta_y(y) = a(y) \quad (3)
\]

- Thus the directional derivative of the functional \( \nu \left( F_t \cdot G \right) \) is obtained by

\[
\frac{\partial \nu \left( F_t \cdot G \right)}{\partial t} \bigg|_{t=0} = \int IF(y; \nu, F) \cdot d \left( G - F \right)(y) . \quad (4)
\]
Appendix
Basic Concepts

- Using the definition of the influence function, the functional $\nu$ can be represented as a von Mises (1947) linear approximation (VOM):

$$\nu(F_t;G) = \nu(F) + t \cdot \int \text{IF}(y; \nu, F) \cdot d (G - F)(y) + r(t; \nu; G, F)$$  \(5\)

where $r(t; \nu; G, F)$ is a remainder term.

- Now consider the leading term of equation (5) as an approximation for $\nu(G)$, that is, for $t = 1$:

$$\nu(G) \approx \nu(F) + \int \text{IF}(y; \nu, F) \cdot dG(y)$$

we will call that first order approximation term, for $G = \Delta_y$, as the Recentered Influence Function (RIF)

$$\text{RIF}(y; \nu, F') = \nu(F') + \text{IF}(y; \nu, F')$$
Appendix
Basic Concepts

- Consider the $\tau^{th}$ quantile: $\nu(F) = q_{\tau}$, which is defined implicitly as the integral bound in
  \[
  \tau = \int_{-\infty}^{q_{\tau}} dF(y) = \int_{-\infty}^{\nu(F)} dF(y) = \int_{-\infty}^{\nu(F_{t,\Delta_y})} dF_{t,\Delta_y}(y)
  \]

- It is easily shown by taking the derivative of this last expression with respect to $t$ and rewriting the resulting expression in terms of $\frac{\partial \nu(F_{t,\Delta_y})}{\partial t}$ that
  \[
  IF(y; q_{\tau}, F) = \left. \frac{\partial \nu(F_{t,\Delta_y})}{\partial t} \right|_{t=0} = \frac{\tau - \mathbb{1}\{y \leq q_{\tau}\}}{f(q_{\tau})}
  \]
  where $f(\cdot)$ is the probability density function associated with the probability distribution $F$. 