

The Gap between the Conditional Wage Distributions of Incumbents and the Newly Hired Employees: Decomposition and Uniform Ordering

Esfandiar Maasoumi, M. Melinda Pitts, and Ke Wu

Working Paper 2014-22
November 2014

Abstract: We examine the cardinal gap between wage distributions of the incumbents and newly hired workers based on entropic distances that are well-defined welfare theoretic measures. Decomposition of several effects is achieved by identifying several counterfactual distributions of different groups. These go beyond the usual Oaxaca-Blinder decompositions at the (linear) conditional means. Much like quantiles, these entropic distances are well defined inferential objects and functions whose statistical properties have recently been developed. Going beyond these strong rankings and distances, we consider weak uniform ranking of these wage outcomes based on statistical tests for stochastic dominance. We focus the empirical analysis on employees with at least 35 hours of work in the 1996–2012 monthly Current Population Survey. Among other findings, we find incumbent workers enjoy a better distribution of wages, but the attribution of the gap to wage inequality and human capital characteristics varies between quantiles. For instance, highly paid new workers are mainly due to human capital components and, in some years, even better wage structure.

JEL classification: I31; C43

Key words: wage gap, metric entropy distance, stochastic dominance, wage distributions, counterfactual analysis, human capital, inequality, labor markets

The views expressed here are the authors' and not necessarily those of the Federal Reserve Bank of Atlanta or the Federal Reserve System. Any remaining errors are the authors' responsibility.

Please address questions regarding content to Esfandiar Maasoumi, Department of Economics, Emory University, Rich Memorial Building, 1602 Fishburne Drive, Room 324A, Atlanta, GA 30322-2240, 404-727-9817, emaasou@emory.edu; M. Melinda Pitts (contact author), Research Department, Federal Reserve Bank of Atlanta, 1000 Peachtree Street NE, Atlanta, GA 30309-4470, 404-498-7009, melinda.pitts@atl.frb.org; or Ke Wu, Department of Economics, Emory University, Rich Memorial Building, 1602 Fishburne Drive, Atlanta, GA 30322-2240, ke.wu@emory.edu.

Federal Reserve Bank of Atlanta working papers, including revised versions, are available on the Atlanta Fed's website at frbatlanta.org/pubs/WP/. Use the WebScriber Service at frbatlanta.org to receive e-mail notifications about new papers.

1 Introduction

Wage differentials among different types of workers, e.g. the gender earnings gap, wage differences between immigrants and natives, etc., have drawn much attention from labor economists and policy makers. There is an extensive literature on labor market outcomes, much of it focused on the analysis of the wage gap at the mean, median and other quantiles of the wage distribution. More recently, techniques have been provided for identifying entire distributions and general function of the distributions. These techniques provide the backdrop for the current paper's approach. One central object of inference in this paper is a summary measure of the "distance" between the entire distributions of interest. Our proposed summary measure makes clear that all other measures of the gap between two distributions are special, and all imply and are implied by well defined welfare functions. Seen in this light, comparison at the mean, median, or any particular quantile would appear to place too much weight on a part of the population, or too equal a weight everywhere. For example, Blau and Kahn (2006) documented the slowing convergence of the gender gap at the mean, median and 90th percentile levels. Albrecht et al. (2003) looked at wages differentials at different parts of the distribution to see whether the gender gap is larger in the upper tail than in the lower tail of the wage distribution due to a "glass ceiling" effect in Sweden. Kampkötter and Sliwka (2011) investigated average wage differences between newly hired and incumbent employees. While these focused examinations are informative and useful, recent papers have examined the wage differentials at the entire distribution level. For example, Massoumi and Wang (2012) employed a metric entropy measure proposed by Granger et al. (2004) to examine the gender wage gap based on the metric distance between two distributions. The measure is the metric member of the Generalized Entropy class of measures with very credible welfare theoretic foundations.

All measures of the gap provide strong ranking of outcome distributions since they are based on implicit "cardinal" welfare or weighting functions. They are inevitably subjective even though some are less extreme than others. In view of this, we explore weak uniform rankings based on the concept of stochastic dominance which allow assessments over entire classes of welfare functions. We do so by rigorous statistical tests for various orders of dominance.

A key issue of interest is about decomposition of observed gaps and rankings in order to identify the factors that underlie the overall wage differentials. Specifically, are those differentials associated with inequality or discrimination in the wage structure, or are they due to human capital composition effect. The classic decomposition method is due to Oaxaca (1973) and Blinder (1973). It is a regression-based method focusing on linear conditional mean decomposition. One major limitation of the Oaxaca-Blinder procedure discussed by Barsky et al. (2002) is that the decomposition provides consistent estimates

of the structure and composition effect only under the assumption that the conditional expectation is linear. As suggested by Barsky et al. (2002), an alternative non-parametric decomposition may be based on propensity score reweighting methods, as advocated in DiNardo et al. (1996). The key advantage of this reweighting approach is that it identifies the counterfactual distribution under less restrictive assumptions and hence can easily be applied to more general distributional statistics, rather than the simple mean and quantiles.

Several recent papers, e.g. Firpo et al. (2007), Massoumi and Wang (2012), have applied this reweighting method for wage gap decompositions. Following the recent approach, this paper decomposes the wage gap between newly hired and incumbent employees across the entire distribution. The wage differences between newly hired and incumbent employees is a less studied topic in labor economics. The seminal work of Doeringer and Piore (1985) provided a theoretical foundation in this area, claiming that the incumbent wage could partially be determined by internal labor markets. Following the work of Baker et al. (1994), many empirical studies investigated the wage structure of the internal labor markets. But very few studies have been done to examine the difference between the wage structure of the internal labor markets and that of the external labor markets. Studying the differential is very important because it sheds light on how much external market forces could determine the wage formation within firms. It could also potentially serve as an indicator of competitiveness of labor markets, since wage differentials between new hires and incumbents with identical characteristics should not exist in perfectly competitive labor markets.

This paper's analysis focuses on a sample of employed workers. As we do not address the issue of selection into the labor market, this work is only generalizable to the work force and not the population as a whole. The plan of the rest of the paper is as follows. In section 2 the decomposition and counterfactual approach is explained. Subsection 2.1 introduces the idea of decomposition with a general distributional function. Subsection 2.2 discusses the Oaxaca-Blinder decomposition that employs linear conditional expectation as the functional form. Subsection 2.3 talks about a metric entropy measure and its welfare implications. Section 3 discusses the empirical and analytical methodologies in details, i.e. the stochastic dominance tests and the propensity score reweighting method used to identify counterfactual distributions. Section 4 explains how to construct the linked CPS monthly data set used in the paper. Section 5 gives the results to the stochastic dominance tests and counterfactual analysis. The conclusion is in Section 6.

2 The Decomposition Problem

A key question of interest in this paper is how to decompose the distributional wage gap between incumbent and newly hired employees into a composition effect, corresponding to

differences in the covariates between the two groups, and a wage structure effect corresponding to differences in the return to the covariates. In this section, we present a general theoretical framework illustrating the decomposition at the distributional level. We also link this decomposition to the more popular Oaxaca-Blinder decomposition method. We then propose to apply an entropy metric, a distributional statistic that could summarize differences between two distributions, to measure the structure and composition effects, and present its welfare function underpinnings.

2.1 Decomposition with General Distributional Function

The outcome variable of interest is the log hourly wage. We have two groups of workers, the incumbent group denoted as group 0 and the new hire group denoted as group 1. Let $\ln(w^0)$ and $\ln(w^1)$ denote the log wages of incumbent and newly hired employees, respectively. We observe a random sample of $N = N_0 + N_1$ workers. N_0 denotes the sample size of incumbents and N_1 is the sample size of the newly hired employees. Let $F_0(y) \equiv Pr[\ln(w^0) \leq y]$ represents the cumulative distribution function (CDF) of $\ln(w^0)$ and $f_0(y)$ is the corresponding probability density function (PDF). The same notations apply to the log wages of newly hired employees.

The wage structure of the incumbent group is denoted by g_0 and that of the newly hired group is denoted by g_1 . Individual wages are determined non-parametrically by both observed characteristics X_i and unobserved characteristics ε_i via the unknown wage structure functions g_d ,

$$\ln(w_i^D) = g_D(X_i, \varepsilon_i) \quad \text{for } D = 0, 1 \quad (1)$$

This non-parametric approach avoids imposing distributional assumptions or specific functional forms, which allow for very flexible interactions among X_i and ε_i . We only assume that $(\ln(w), X, D)$ have some unknown joint distribution. Under such specification, the wage differential is assumed to be associated to two primary sources: (1) differences in observed human capital characteristics X_i (e.g. education, age, etc.), and unobserved human capital characteristics ε_i (e.g. innate ability). However, under the unconfoundedness assumption elaborated in the next section, the composition effect only comes from differences in X_i and differences in the wage structures, $g_D(\cdot)$.

With observed data, we can identify the conditional distribution of a new hire's log hourly wage, $\ln(w^1)|X, D = 1 \stackrel{d}{\sim} F_{1|X}$, and the conditional distribution of the incumbent's log hourly wage, $\ln(w^0)|X, D = 0 \stackrel{d}{\sim} F_{0|X}$. With certain further assumptions discussed later, we are able to identify the conditional counterfactual distribution of $\ln(w^0)|X, D = 1 \stackrel{d}{\sim} F_{C|X}$ using the aforementioned propensity score reweighting method. The conditional

counterfactual distribution $F_{C|X}$ is the wage distribution that would have been observed under the wage structure of group 0, but with the distribution of observed and unobserved characteristics of group 1. Accordingly, the unconditional (on X) distributions are denoted as F_1 , F_0 , and F_c . We analyze the distributional wage gap between groups 0 and 1 using some distributional function. Following Firpo et al. (2007), we denote ν as a function of the conditional joint distribution of $(\ln(w^1), \ln(w^0)) | D$, i.e. $\nu : F_\nu \rightarrow \mathbb{R}$, where F_ν belongs to a class of distribution functions that satisfy $\forall F \in F_\nu$ and $\|\nu(F)\| < +\infty$. Under this specification, the distributional wage gap between two groups can be written in terms of ν :

$$\Delta_O^\nu = \nu(F_1) - \nu(F_0) = \nu_1 - \nu_0 \quad (2)$$

We can then further decompose equation 2 into two parts, given that X is not evenly distributed across the two groups:

$$\Delta_O^\nu = (\nu_1 - \nu_C) + (\nu_C - \nu_0) = \Delta_S^\nu + \Delta_X^\nu \quad (3)$$

where the first term Δ_S^ν reflects the wage structure effect, meaning the effect caused by changing $g_1(\cdot, \cdot)$ to $g_0(\cdot, \cdot)$ while holding characteristics $(X, \varepsilon) | D = 1$ constant. The other term Δ_X^ν indicates the composition effect, which is the effect from changing the distribution of characteristics from $(X, \varepsilon) | D = 1$ to $(X, \varepsilon) | D = 0$, while keeping the “wage structure” $g_0(\cdot, \cdot)$ constant.

2.2 Oaxaca-Blinder Decomposition as a Linear Conditional Expectation Case

With such settings, we can include Oaxaca-Blinder decomposition as a special case, where the ν function is the mathematical expectation \mathbb{E} . Under the assumption that the conditional expectation takes linear form, we have

$$\mathbb{E}[\ln(w_i^D) | X] \equiv X_i \beta_D, \quad \text{for } D = 0, 1 \quad (4)$$

Then the expected wage gap between the “treated” and untreated group, Δ_O^μ , can be

written as

$$\begin{aligned}
\Delta_O^\mu &= \mathbb{E}_x[\mathbb{E}[(\ln(w)|X, D = 1)] - \mathbb{E}_x[\mathbb{E}[(\ln(w)|X, D = 0)]] \\
&= \mathbb{E}[\ln(w)|D = 1] - \mathbb{E}[\ln(w)|D = 0] \\
&= \mathbb{E}[X|D = 1]\beta_1 - \mathbb{E}[X|D = 0]\beta_0 \\
&= \mathbb{E}[X|D = 1](\beta_1 - \beta_0) + (\mathbb{E}[X|D = 1] - \mathbb{E}[X|D = 0])\beta_0 \\
&\equiv \Delta_S^\mu + \Delta_X^\mu
\end{aligned}$$

The second line follows from the Law of Iterated Expectations. Note that the decomposition in the fourth line uses group 1 as the base group. The counterfactual outcome indicates the mean wage that would have been observed under the wage structure of group 0, but with X from group 1, can directly be computed by $\mathbb{E}[X|D = 1]\beta_0$, which is the counterpart of ν_C in equation 3. Δ_S^μ is the mean wage structure effect and accordingly Δ_X^μ stands for the mean composition effect. Oaxaca-Blinder decomposition is very appealing empirically due to its ease of estimation and interpretation. However, as Barsky et al. (2002) pointed out, consistent estimates of both effects rely on the assumption of the linear structure, which is restrictive. Moreover, Kline (2011) showed that the counterfactual mean identified by the Oaxaca-Blinder method constitutes a propensity score reweighting estimator based upon a linear model for the conditional odds of being treated. Therefore, Oaxaca-Blinder decomposition is indeed a special linear case of propensity score reweighting method. By applying the reweighting method generally, we impose less structure and hence lead to more robust inference.

3 Empirical Methodology

3.1 A Metric Entropy Measure of the Wage Gap

A comparison of means is implicitly based on a welfare/weighting function that is additive and attaches equal weight to each wage earner. Among others, this implicit welfare function imposes infinite substitutability. Assessment at the median, or any other quantile is justified by even more radical welfare weighting schemes. To overcome these limitations we choose more general distributional functions that could summarize information along the whole distribution. Several commonly used information-based entropy measures such as Shannon’s entropy and Kullback-Leibler relative entropy are good candidates for such distributional functions. They are well analyzed in the field of income inequality where the corresponding welfare functions are identified. For instance, an axiomatic approach to “ideal” inequality measures, equivalently welfare functions, or risk averse utility functions, renders the class of Generalized Entropy as ideal. Further additive decomposition

requirements render Shannon’s entropy, and Theil’s measures of inequality as “best”. (For example, see Bourguignon (1979), Shorrocks (1978), and Maasoumi (1986)) Inequality measures are divergence measures between any distribution and a uniform (rectangular) size distribution representing perfect equality. The latter is eliminated when the difference between the “inequalities” of two wage distributions is computed. However, entropy divergence measures are generally not metric since they violate the triangular inequality. Hence they are not proper measures of distance. This paper uses a metric entropy measure S_ρ proposed by Granger et al. (2004) as the specific distributional ν function, which is a normalization of the “Bhattacharya-Matusita-Hellinger” measure of distance. It is the one member of the Generalized Entropy family that is a metric. It is given by

$$S_\rho = \frac{1}{2} \int_{-\infty}^{\infty} (f_1^{\frac{1}{2}} - f_0^{\frac{1}{2}})^2 dy \quad (5)$$

This measure has several desirable properties: 1. it is well defined for both continuous and discrete variables;ⁱ 2. it is normalized to 0 if two distributions are equal and lies between 0 and 1; 3. it satisfies the properties of a metric and hence is a true measure of distance; and 4. it is invariant under continuous and strictly increasing transformation on the underlying variables. Note that the natural log of earnings is used through out this paper. Since the logarithm is a strictly increasing function, the findings of this paper are invariant whether using the raw wages or the log form. Following Granger et al. (2004) and Maasoumi and Racine (2002), we consider a kernel based nonparametric implementation of the entropy measure shown in equation 5.

3.2 Stochastic Dominance

Using S_ρ as the distributional distance measure, we can estimate the distance between original wage distribution and counterfactual wage distribution, and thus the distributional wage structure and composition effects. However, this analysis is still subjective as it would reflect the social welfare based on the generalized entropy function.

In order to compare the different wage distributions robustly, and relative to large classes of welfare functions, we need to examine Stochastic Dominance rankings. First order Stochastic Dominance corresponds to a class (denoted as U_1) of all (increasing) von Neumann-Morgenstern type of social welfare functions u such that welfare is increasing in wages (i.e. $u' > 0$), and the second order Stochastic Dominance test corresponds to the class of social welfare functions in U_1 such that $u'' \leq 0$ (i.e. concavity), denoted as U_2 . Concavity implies an aversion to higher dispersion (or inequality) of wages across workers. In this paper, we focus on the one-dimensional social welfare function of only earnings.

ⁱFor discrete variables, $S_\rho = \frac{1}{2} \sum (p_1^{1/2} - p_0^{1/2})^2$.

Case 1. First Order Dominance: Incumbent employee wage distribution First Order Stochastically Dominates newly hired employee wage distribution (denoted as $ln(w^0)$ FSD $ln(w^1)$) if and only if

1. $E[u(ln(w^0))] \geq E[u(ln(w^1))]$ for all $u \in U_1$ with strict inequality for some u ;
2. Or, $F_0(y) \leq F_1(y)$ for all y with strict inequality for some y .

Case 2. Second Order Dominance: Incumbent wage distribution Second Order Stochastically Dominates newly hired employee wage distribution (denoted as $ln(w^0)$ SSD $ln(w^1)$) if and only if

1. $E[u(ln(w^0))] \geq E[u(ln(w^1))]$ for all $u \in U_2$ with strict inequality for some u ;
2. Or, $\int_{-\infty}^y F_0(t)dt \leq \int_{-\infty}^y F_1(t)dt$ for all y with strict inequality for some y .

The stochastic dominance tests used in this paper are based on a generalized Kolmogorov-Smirnov test as discussed in Linton et al. (2005). The test statistics for FSD and SSD are given by

$$d = \sqrt{\frac{N_0 N_1}{N_0 + N_1}} \min\{\sup[F_0(y) - F_1(y)], \sup[F_1(y) - F_0(y)]\} \quad (6)$$

$$s = \sqrt{\frac{N_0 N_1}{N_0 + N_1}} \min\{\sup \int_{-\infty}^y [F_0(t) - F_1(t)]dt, \sup \int_{-\infty}^y [F_1(t) - F_0(t)]dt\} \quad (7)$$

When we report the empirical test results in Section 5, we denote $\sup[F_0(y) - F_1(y)]$ as $d_{1,max}$ and $\sup[F_1(y) - F_0(y)]$ as $d_{2,max}$. We report both $d_{1,max}$ and $d_{2,max}$ along with the test statistic d for clarity of interpretation. $s_{1,max}$ and $s_{2,max}$ are similarly defined. In empirical applications, the CDFs are replaced with their empirical counterparts. The empirical CDFs are given by $\widehat{F}_d(y) = \frac{1}{N_d} \sum_{i=1}^{N_d} I(ln(w_i^d) \leq y)$, $d = 0, 1$, where $I(\cdot)$ is an indicator function. The underlying distribution of the test statistics are generally unknown and depend on the data. Following Maasoumi and Heshmati (2000), simple bootstrap technique based on 199 replications are employed to obtain the empirical distribution of the test statistics.

3.3 Identification of the Counterfactual Distributions

The fundamental question this paper addresses is to identify the wage structure and composition effects through the identification of counterfactual wage distributions, and determine which effect dominates the wage differential. We consider the following counterfactual situation: holding the human capital characteristics of the newly hired workers constant, if we change their wage structure to the wage structure of the incumbents, would the counterfactual wage distribution be different from the original one? If so, would the counterfactual

wage distribution stochastically dominate the original one in terms of welfare? If we find such dominance in the first or second order, we would conclude that the wage structures are different and the internal wage structure is better. Similarly, we could also check whether the wage gap is due to differences in human capital characteristics by changing the distribution of the newly hired employees' characteristics to that of the incumbents, holding their wage structure unchanged. To conduct such counterfactual analysis, we follow the propensity score reweighting methods as discussed in Firpo (2007) to identify the counterfactual distributions mentioned above. Simple bootstrap with replacement is applied to obtain the statistical significance of the dominance tests. Specifically, we want to identify the distributions of the following two counterfactual outcomes:

$$\ln(w_i^{c1}) = g_0(X_i, \varepsilon_i) | D = 1 \quad (\text{counterfactual outcome \#1}) \quad (8)$$

$$\ln(w_i^{c2}) = g_1(X_i, \varepsilon_i) | D = 0 \quad (\text{counterfactual outcome \#2}) \quad (9)$$

The benchmark outcome we considered is the conditional wage distribution of the new hires $\ln(w_i^1) = g_1(X_{i1}, \varepsilon_{i1})$. The counterfactual outcome #1, $\ln(w_i^{c1})$, indicates the hypothetical unobserved wage of the newly hired employees if they were paid under the incumbent wage structure. Comparing the benchmark wage $\ln(w_i^1)$ to $\ln(w_i^{c1})$ using the S_ρ measure would yield the wage structure effect Δ_S^ν as in equation 3. Comparing distributional distance between $\ln(w_i^{c1})$ and the incumbent wage $\ln(w_i^0)$ would give us the composition effect, denoted by Δ_X^ν in equation 3. However, that would require using $\ln(w_i^0)$ as the benchmark. For ease of interpretation, we choose to use $\ln(w_i^1)$ as the benchmark when identifying both effects and construct counterfactual outcome #2 $\ln(w_i^{c2})$, which indicates the hypothetical wage of the newly hired employees if they had the characteristics of the incumbents. With the new hire wage as the benchmark, S_ρ measure of $\ln(w_i^1) - \ln(w_i^{c2})$ gives the composition effect that are reported in empirical applications in Section 5.

Firpo (2007) proved that under certain assumptions, such counterfactual distributions are identified. Following Firpo (2007) and Firpo et al. (2007), we make similar assumptions:

1. Unconfoundedness: Suppose (Y, D, X) have a joint distribution, where Y is the outcome and D is a dummy indicating treatment: (Y_1, Y_0) and D are jointly independent conditional on $X = x$.
2. Common support: For all $x \in X$, $0 < Pr\{D = 1 | X = x\} := p(x) < 1$.

Assumption 1 means that fixing the values of observable human capital characteristics X , the distribution of the wage outcome or the error term ε is independent of whether one is incumbent or newly hired. Assumption 2 rules out the possibilities that some specific

x belongs only to either one of the two worker groups and hence such x can predict the probability of being treated perfectly.

The counterfactual distribution of $\ln(w_i^{c1})$ could be identified by the following propensity score reweighting methods discussed in Firpo (2007).

$$F_{c1} = \mathbb{E}[\omega_{c1}(D_1, X) \cdot I[(\ln(w_i) \leq y)]] \quad (10)$$

where $\omega_{c1}(D_1, X) = \left(\frac{p_1(x)}{1-p_1(x)}\right) \left(\frac{1-D_1}{p_1}\right)$, D_1 is a treatment dummy variable taking the value of 1 for incumbent employees, $p_1(x) = Pr\{D_1 = 1|X = x\}$ is the propensity score, $p_1 = Pr\{D_1 = 1\} = \mathbb{E}[p_1(X)]$ is the marginal probability of being treated. In practice, we will estimate the propensity score parametrically using a logit model.ⁱⁱ Applying the weights $\omega_{c1}(D_1, X)$ gives us the counterfactual distribution of $\ln(w_i^{c1})$. Identifying the distribution of counterfactual outcome $\ln(w_i^{c2})$, F_{c2} , is similar, but we need to take newly hired employees as the treated group. Let D_2 be the treatment dummy taking the value of 1 for new hires.

$$F_{c2} = \mathbb{E}[\omega_{c2}(D_2, X) \cdot I[(\ln(w_i) \leq y)]] \quad (11)$$

where $\omega_{c2}(D_2, X) = \left(\frac{p_2(x)}{1-p_2(x)}\right) \left(\frac{1-D_2}{p_2}\right)$, $p_2(x)$ and p_2 are similarly defined as in the previous case.ⁱⁱⁱ Applying the weights $\omega_{c2}(D_2, X)$ gives us the counterfactual distribution of $\ln(w_i^{c2})$. Once we identify the counterfactual distributions of interest, we can then perform stochastic dominance tests to compare those counterfactual distributions with the original distribution.

4 Data

The data used in this paper come from 1996-2012 monthly Current Population Survey (CPS). The monthly CPS is a survey of a probability sample of housing units. Although the CPS is designed to be a cross-sectional survey, it does not survey a completely new set of housing units every month. The sample is divided into eight representative rotation groups. Therefore, a typical housing unit in the sample is interviewed in 8 different months, given no attrition during survey period. If a housing unit is randomly selected into monthly CPS for the first time, it will be interviewed for four consecutive months, followed by an 8-month break, and then be surveyed for another four consecutive months. The rotation group could be identified by the CPS variable “month in sample” (MIS).

The CPS sample design actually allows us to longitudinally link a household in sample

ⁱⁱNonparametric kernel regression can also be used to estimate the propensity score, which allows more flexible dependence relations among independent and dependent variables.

ⁱⁱⁱNote that under such setting, $p_1(x) + p_2(x) = 1$ and $p_1 + p_2 = 1$.

over 8 different months. Following methods as discussed in Madrian and Lefgren (1999), we conducted one-month matching for all the eligible rotation groups (MIS = 2-4 or 6-8) in each monthly sample, i.e. linking those eligible subsamples with their previous month observations.^{iv} In our sample, the matching rate for those eligible groups is over 90 percent on average.^v Using this longitudinally linked data set, we could identify the incumbent and newly hired employees. Since we are interested in the wage differentials, we first restrict our sample to individuals of working age, i.e. those who aged from 18 to 64. Then we keep those who remained full-time employed (35 hours per week or above) in both month $t - 1$ and month t . Among those full-time workers, we define incumbent workers to be those who stayed with the same employer from month $t - 1$ to t . The newly hired employees are defined to be those who changed their employer from month $t - 1$ and t , i.e. workers that switched to a new job with a new employer at time t .^{vi}

Following the literature (e.g. Massoumi and Wang (2012)), we use the log of hourly wages, measured by an individual’s weekly wage income divided by the number of hours worked per week. Note that, as we mentioned above, the metric entropy measure of the wage differential and stochastic dominance tests are invariant to the logarithm transformation, while many conventional measures are not. The observed human capital variables used in the counterfactual analysis include age, age squared, gender, education (five education groups: less than high school, high school, some college, college, graduate), marital status, ethnicity and region (Northeast, Midwest, South and West). Occupation variable is grouped into three categories: high-skill (managerial and professional occupations); medium-skill (technician, technical production, sales, and administrative support occupations); and low-skill (other occupations such as maintenance, construction, and farming occupations).

5 Results

5.1 Baseline Analysis

5.1.1 Trend of the Wage Differential between Internal and External Labor Markets

Table 1 shows various measures of the log wage differences between the incumbent and newly hired employees, i.e. $\ln(w^0) - \ln(w^1)$. The second column in the table reports the

^{iv}In 1995, the Census made some changes to CPS sample ID variable, which leads to very poor matching rates for that year, so we chose 1996 as the starting year to circumvent the problem.

^vOne shortcoming of this linked data is that we can only follow workers who remain in the same household. Thus any new hire that moved in order to take a new job could not be matched in this data set.

^{vi}We also exclude those with hourly wage less than or equal to 1 dollar, because those extremely low wages are likely be due to misreporting.

distributional measure of the wage gap S_ρ . Since S_ρ is a normalized metric taking on values between 0 and 1, for easy interpretation we report the original results multiplied by 100 throughout the paper. Under the null hypothesis of no difference between incumbent and new hire wage distributions, we calculate the statistical significance of the S_ρ measure using 199 simple bootstrap replications. The p values are reported in the third column. The other columns in Table 1 report conventional measures (e.g. mean, median and quantiles at various levels) of earning differentials commonly used in the literature. We can see that both the traditional measures and the metric entropy measure S_ρ imply that there exists wage differentials between those two groups of workers for all the years in sample. The distributional distances are statistically significant at 5% in 2011 and at 1% in remaining years. The mean differences and all the quantile differences except for the 90th quantile in 2010, are all positive, clearly showing wage gaps that in favor of the incumbent employees. However, it is hard to tell a clear trend over time for any of these measures and even harder to tell whether our new measure shows a different pattern of the time trend from other traditional measures.

Table 1: Entropy Measures of Wage Differentials

Year	$S_\rho \times 100$	p of S_ρ	mean	10th	25th	50th	75th	90th
1996	0.97	(0.00)	0.14	0.09	0.13	0.14	0.13	0.11
1997	1.47	(0.00)	0.15	0.13	0.16	0.18	0.17	0.08
1998	1.11	(0.00)	0.13	0.08	0.15	0.20	0.11	0.04
1999	1.14	(0.00)	0.13	0.15	0.12	0.17	0.13	0.07
2000	0.93	(0.00)	0.11	0.07	0.17	0.12	0.07	0.07
2001	0.69	(0.00)	0.10	0.07	0.12	0.11	0.08	0.04
2002	1.03	(0.00)	0.10	0.11	0.11	0.13	0.08	0.04
2003	0.95	(0.00)	0.11	0.13	0.12	0.14	0.10	0.04
2004	0.62	(0.00)	0.10	0.06	0.08	0.12	0.13	0.07
2005	0.97	(0.00)	0.12	0.06	0.14	0.12	0.12	0.12
2006	0.98	(0.00)	0.14	0.09	0.10	0.15	0.14	0.14
2007	0.50	(0.00)	0.10	0.09	0.15	0.11	0.08	0.06
2008	0.65	(0.01)	0.09	0.06	0.13	0.12	0.07	0.03
2009	1.24	(0.00)	0.11	0.11	0.18	0.16	0.06	0.09
2010	0.64	(0.00)	0.07	0.10	0.11	0.13	0.04	-0.08
2011	0.59	(0.03)	0.08	0.05	0.07	0.07	0.08	0.09
2012	0.65	(0.00)	0.09	0.06	0.13	0.11	0.08	0.05

Notes: Columns (2)-(3) report metric entropy measure of distributional distance and its p values respectively. The p values are obtained from 199 simple bootstrap under the null hypothesis of no difference between incumbent and new hire wage distributions

The S_ρ measure and other conventional measures are not directly comparable. Thus, to enable easy comparisons, we normalize all these measures by setting the value in the year of 1996 to 100 and computing the normalized values. The plot of these normalized

values of S_ρ , mean, median, 25th and 75th percentiles in Figure 1. As shown in the graph, other than the 75th percentile, the traditional measures display similar time trends as the S_ρ entropy measure. In order to check how the wage differentials fit with macro business cycles, we plot the recession periods with shaded vertical bars in the figure. During the sample period, Mar 2001 to Nov 2001 and Dec 2007 to Jun 2009 are considered as recession periods by the NBER. Since our measures are computed at yearly frequency, we roughly pick 2001, 2008 and 2009 as the recession years and the three years are indicated by the shaded bars in Figure 1. The line plots do not show very clear cyclical patterns, but all measures, except the 75th percentile of wage differentials do seem to increase during the recent great recession period from 2008 to 2009. During the great recession the level of payroll employment fell by 5.4%, more than four times the employment decline faced in the 2001 recession.^{vii} Many firms reduced or halted hiring, which reduced the bargaining power of those job seekers. So the newly hired employees may have had to accept lower wages, which increases the wage gaps between the incumbent and the newly hired workers.

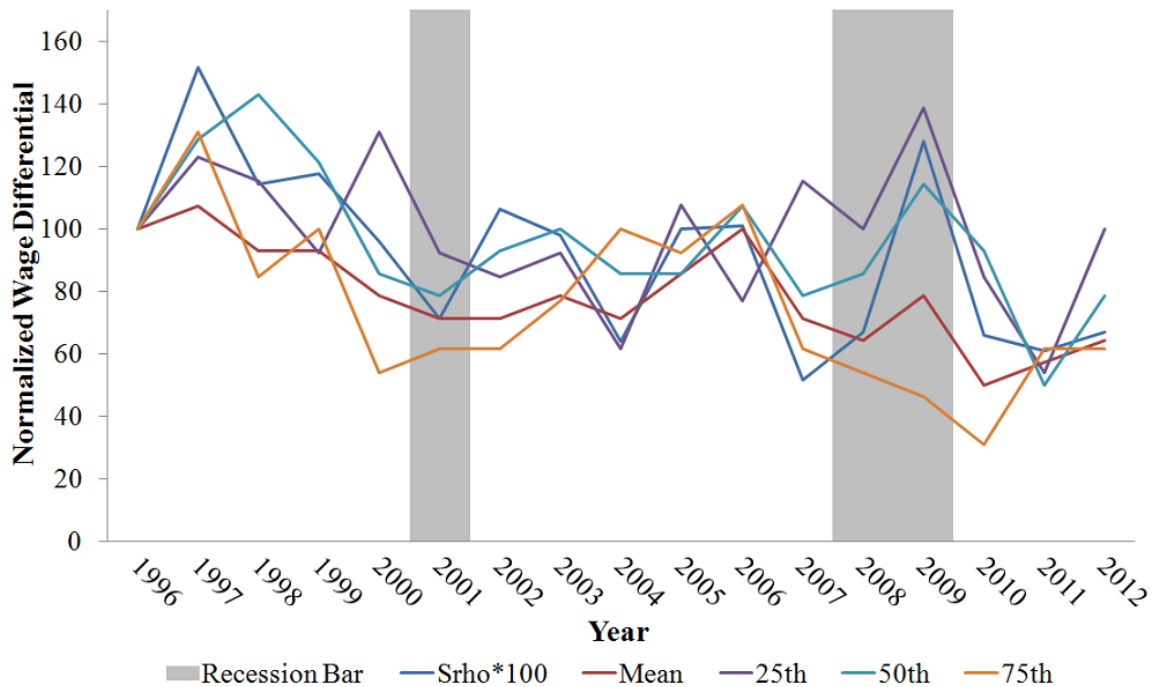


Figure 1: Time Trend of Wage Differential with Business Cycle Indicator

5.1.2 Stochastic Dominance Test Results

As discussed above, these measures of the gender gap could not give a clear ranking of the earnings distributions in terms of social welfare. Therefore, in Table 2 we present the

^{vii} Authors' calculation; Source: BLS, Haver Analytics

stochastic dominance test results. The second column labeled Observed Ranking details if the distributions can be ranked in either the first or second order, where FSD is short for First-order Stochastic Dominance and SSD stands for Second-order Stochastic Dominance. The columns labeled $Pr[d \leq 0]$ and $Pr[s \leq 0]$ report the probabilities of the test statistics (of the first and second order dominance tests respectively) to be non-positive based on the simple bootstrap with replacement for 199 replications. The probability serves a similar role as p-values in any hypothesis test, but the interpretation is reversed. For example, if we observe FSD (SSD) and $Pr[d \leq 0]$ ($Pr[s \leq 0]$) is 0.95, then it means that the test statistic is statistically significant at 5% level (p-value=0.05).

Table 2: Stochastic Dominance Test Results

Year	Observed Rank	$d_{1,max}$	$d_{2,max}$	d	$P(d \leq 0)$	$s_{1,max}$	$s_{2,max}$	s	$P(d \leq 0)$
1996	FSD	-0.03	5.15	-0.03	0.30	-0.04	104.05	-0.04	0.94
1997	SSD	0.06	6.30	0.06	0.25	-0.05	110.07	-0.05	0.99
1998	SSD	0.11	5.47	0.11	0.04	-0.05	98.14	-0.05	0.87
1999	SSD	0.06	5.78	0.06	0.19	-0.05	93.93	-0.05	0.81
2000	SSD	0.11	4.96	0.11	0.05	-0.06	86.00	-0.06	0.96
2001	SSD	0.01	4.39	0.01	0.43	-0.06	80.49	-0.06	0.97
2002	SSD	0.24	4.48	0.24	0.01	-0.06	76.70	-0.06	0.99
2003	SSD	0.07	4.20	0.07	0.14	-0.05	71.31	-0.05	0.87
2004	FSD	-0.06	4.27	-0.06	0.41	-0.06	68.43	-0.06	0.79
2005	SSD	0.09	4.54	0.09	0.18	-0.09	73.32	-0.09	0.92
2006	SSD	0.08	4.62	0.08	0.21	-0.09	95.11	-0.09	0.94
2007	FSD	-0.06	3.88	-0.06	0.55	-0.07	67.61	-0.07	0.87
2008	FSD	-0.03	4.16	-0.03	0.48	-0.08	55.20	-0.08	0.98
2009	SSD	0.38	3.56	0.38	0.00	-0.04	61.14	-0.04	0.76
2010	SSD	0.45	2.76	0.45	0.01	-0.06	47.83	-0.06	0.93
2011	SSD	0.07	2.13	0.07	0.09	-0.07	35.03	-0.07	0.54
2012	SSD	0.01	3.34	0.01	0.21	-0.06	47.96	-0.06	0.64

From Table 2, we can see that the wage distribution of incumbents lies predominantly to the right of the wage distribution of new hires, meaning that incumbent workers enjoy higher level of wages. For all the years in sample, we find stochastic dominance relations either in the first or second order. In 4 out of 17 years (1996, 2004, 2007 and 2008), we find the wage distribution of incumbent workers to empirically dominates, in a first-order sense, the wage distribution among newly hired workers, but such dominance relation is not statistically significant in any of the 4 years. For the remaining years, highly significant second-order dominance is found in the years of 1997, 2000-2002 and 2008, with confidence level greater than 0.95. This suggests that any worker with a social welfare function in the class U_2 (increasing and concave in wage) would prefer the incumbent distribution to

the new hire distribution in those 5 years. Such dominance ranking is only possible when we account for an aversion to higher dispersion in the welfare criteria. This finding is quite interesting because those significant second-order dominance cases mainly occurred around recession periods (2001 and 2008 are recession years). Second-order dominance indicates that starting from the very left tail of the wage distribution, incumbent workers are better paid than newly hired workers at most quantiles. This is in line with the findings of Oreopoulos et al. (2006), which found that young graduates entering the labor market in a recession suffer significant initial earnings losses. SSD also suggests that at the far right tail of the wage distribution, some newly hired workers could be paid better than their incumbent counterparts. One possible explanation could be the differences in human capital characteristics. Those who managed to find highly paid jobs during a recession may have very strong human capital characteristics. We will further test this hypothesis using counterfactual analysis in a latter section.

5.2 Counterfactual Analysis

Table 3 reports the estimated wage structure effect, i.e. the wage gap caused by the inequality in the pay structure. Metric entropy and traditional measures of the log wage differences between the newly hired employees and their counterfactual outcome #1, i.e. $\ln(w^1) - \ln(w^{c1})$, are presented. The p values of S_ρ measure are calculated using the same bootstrap method as applied in Table 1. From Table 3, we can see that most means and quantiles in almost all years except for 2011 are negative, which means that the counterfactual wages under the incumbent's wage structure while keeping new employee characteristics unchanged are generally better than actual wages those new hires earn. The distributional distance measured by S_ρ is smaller and less significant than the distance between $\ln(w^0)$ and $\ln(w^{c1})$, as it only reflects the wage structure effect.

Table 4 reports dominance test results of the actual wage distribution of the new hires versus the counterfactual wage distribution #1. Recall that this comparison identifies the difference of the wage structures between the external and internal labor markets. Any finding of stochastic dominance indicates the inequality in the pay structure instead of the differences in human capital characteristics. We find the counterfactual wage distribution #1 SSD the original wage distribution of the new hires for all the years in sample, except for the year of 2011, which means that if the newly hired workers were paid under incumbent wage structure, such outcomes are preferred at least for those with social welfare functions in the class of U_2 . As indicated by the bootstrapped probabilities, those dominance relations are statistically significant in 1997, 2006 and 2008, with confidence level greater than 0.9 and are close to significant in 2000 and 2001. Second-order dominance indicates that such findings holds mainly at the lower tail of the wage distribution, while

Table 3: Measures of Differences between New Hire and New Hire counterfactual #1 Distributions

Year	$S_\rho \times 100$	p of S_ρ	mean	10th	25th	50th	75th	90th
1996	0.34	(.03)	-0.06	-0.05	-0.07	-0.06	-0.05	-0.02
1997	0.77	(.00)	-0.07	-0.09	-0.11	-0.10	-0.08	0.00
1998	0.47	(.01)	-0.05	-0.04	-0.06	-0.09	-0.03	0.04
1999	0.47	(.01)	-0.06	-0.07	-0.06	-0.09	-0.04	0.00
2000	0.46	(.01)	-0.03	-0.07	-0.11	-0.04	0.00	0.04
2001	0.32	(.05)	-0.03	-0.00	-0.04	-0.04	-0.01	0.05
2002	0.47	(.00)	-0.03	-0.07	-0.08	-0.05	0.00	0.00
2003	0.38	(.06)	-0.02	-0.08	-0.05	-0.05	0.00	0.05
2004	0.23	(.25)	-0.03	-0.05	-0.03	-0.05	-0.04	0.03
2005	0.36	(.04)	-0.04	-0.06	0.00	-0.04	-0.03	-0.03
2006	0.28	(.17)	-0.03	0.00	-0.04	-0.07	-0.02	-0.00
2007	0.19	(.58)	-0.03	-0.05	-0.10	-0.03	-0.02	0.03
2008	0.37	(.17)	-0.03	-0.06	-0.07	-0.05	0.00	0.07
2009	0.63	(.00)	-0.04	-0.07	-0.09	-0.08	0.00	-0.00
2010	0.40	(.11)	-0.00	-0.05	-0.04	-0.03	0.04	0.12
2011	0.47	(.00)	0.01	0.00	0.00	0.04	0.04	0.01
2012	0.33	(.06)	-0.03	-0.02	-0.04	-0.03	0.01	0.00

Notes: Columns (2)-(3) report metric entropy measure of distributional distance and its p values respectively. The p values are obtained from 199 simple bootstrap under the null hypothesis of no difference between the new hire and their counterfactual #1 wage distributions

at the upper tail, the wage structure of those new hires may actually be better than those of the incumbents, so such counterfactual wages may be lower than their actual wages for those highly paid new employees. To further test this finding, in the following subsection we divide our sample into two sub groups, higher and lower wage groups, and conducted counterfactual analysis respectively.

Table 4: Stochastic Dominance Test Results, Counterfactual #1

Year	Observed Rank	$d_{1,max}$	$d_{2,max}$	d	$P(d \leq 0)$	$s_{1,max}$	$s_{2,max}$	s	$P(d \leq 0)$
1996	SSD	14.22	0.58	0.58	0.05	240.39	-0.28	-0.28	0.85
1997	SSD	17.43	0.73	0.73	0.03	261.86	-0.25	-0.25	0.96
1998	SSD	16.37	2.39	2.39	0.01	206.92	-0.25	-0.25	0.71
1999	SSD	15.41	1.31	1.31	0.01	201.00	-0.46	-0.46	0.60
2000	SSD	11.39	1.92	1.92	0.00	156.57	-0.34	-0.34	0.88
2001	SSD	8.80	2.64	2.64	0.02	132.64	-0.30	-0.30	0.89
2002	SSD	9.60	2.66	2.66	0.00	136.40	-0.26	-0.26	0.81
2003	SSD	9.20	2.70	2.70	0.00	123.87	-0.26	-0.26	0.72
2004	SSD	8.55	1.16	1.16	0.01	109.38	-0.32	-0.32	0.61
2005	SSD	10.93	1.43	1.43	0.01	143.21	-0.34	-0.34	0.77
2006	SSD	12.29	1.38	1.38	0.01	159.84	-0.45	-0.45	0.91
2007	SSD	9.16	1.75	1.75	0.03	104.39	-0.33	-0.33	0.73
2008	SSD	11.21	3.73	3.73	0.00	113.81	-0.43	-0.43	0.94
2009	SSD	11.15	3.16	3.16	0.00	155.81	-0.28	-0.28	0.63
2010	SSD	5.33	7.22	5.33	0.00	98.05	-0.29	-0.29	0.46
2011	None	3.39	4.66	3.39	0.00	29.92	25.71	25.71	0.16
2012	SSD	8.42	0.85	0.85	0.00	80.50	-0.22	-0.22	0.43

Table 5 reports the estimated composition effect, i.e. the wage gap caused by the differences human capital characteristics. S_ρ and conventional measures of the log wage differences between the newly hired employees and their counterfactual outcome #2, i.e. $\ln(w^1) - \ln(w^c)$, are reported. From the table we can see that all the means and quantiles in all the years in the sample are negative, which indicates that the counterfactual wages under the incumbent characteristics while keeping new hire's wage structure unchanged are generally better than actual wages of the new hires. We conclude that the differences in human capital characteristics between the incumbents and new hires also contributed to the their wage gap. The distributional distance measured by S_ρ is a little smaller and less significant than those reported in Table 3, which means that the estimated composition effect is smaller compared to the estimated wage structure effect.

Table 6 reports the stochastic dominance test results from the comparison between the actual wage distribution of the new hires versus the counterfactual wage distribution #2. Note that this comparison identifies the wage gap caused by differences in human capital

Table 5: Measures of Difference between New Hire and New Hire counterfactual #2 Distributions

Year	$S_\rho \times 100$	p of S_ρ	mean	10th	25th	50th	75th	90th
1996	0.27	(0.53)	-0.08	-0.04	-0.07	-0.07	-0.08	-0.08
1997	0.28	(0.59)	-0.08	-0.09	-0.07	-0.10	-0.14	-0.08
1998	0.29	(0.64)	-0.08	-0.04	-0.06	-0.13	-0.10	-0.06
1999	0.28	(0.44)	-0.08	-0.07	-0.03	-0.09	-0.12	-0.11
2000	0.23	(0.48)	-0.08	-0.06	-0.11	-0.05	-0.09	-0.08
2001	0.24	(0.08)	-0.08	0.00	-0.05	-0.10	-0.09	-0.08
2002	0.28	(0.42)	-0.09	-0.05	-0.11	-0.10	-0.10	-0.10
2003	0.23	(0.50)	-0.07	-0.07	-0.05	-0.09	-0.10	-0.07
2004	0.27	(0.66)	-0.08	-0.06	-0.03	-0.11	-0.12	-0.08
2005	0.26	(0.14)	-0.08	-0.06	-0.01	-0.07	-0.10	-0.11
2006	0.29	(0.05)	-0.09	-0.03	-0.04	-0.10	-0.11	-0.12
2007	0.26	(0.26)	-0.08	-0.05	-0.10	-0.09	-0.10	-0.07
2008	0.20	(0.97)	-0.07	-0.03	-0.08	-0.10	-0.11	-0.06
2009	0.25	(0.68)	-0.09	-0.07	-0.09	-0.11	-0.11	-0.12
2010	0.19	(0.80)	-0.08	-0.05	-0.07	-0.09	-0.10	-0.09
2011	0.19	(0.98)	-0.07	-0.04	-0.05	-0.08	-0.09	-0.10
2012	0.20	(0.51)	-0.07	-0.00	-0.06	-0.10	-0.09	-0.10

Notes: Columns (2)-(3) report metric entropy measure of distributional distance and its p values respectively. The p values are obtained from 199 simple bootstrap under the null hypothesis of no difference between between the new hire and their counterfactual #2 wage distributions

characteristics. As shown in the table, we find the counterfactual wage distribution #2 FSD the actual new hire wage distribution in all year. However, such first-order dominance relations are not statistically significant. FSD always indicates SSD, but those second-order dominance relations are largely insignificant as well. Hence we have found some evidence for differences in human capital characteristics, but the evidence is not quite strong. The data seem to tell us that even though there is some difference in human capital between incumbent and newly hired workers, such a difference is not large enough to be statistically meaningful.

Table 6: Stochastic Dominance Test Results, Counterfactual #2

Year	Observed Rank	$d_{1,max}$	$d_{2,max}$	d	$P(d \leq 0)$	$s_{1,max}$	$s_{2,max}$	s	$P(d \leq 0)$
1996	FSD	14.50	-0.30	-0.30	0.21	303.47	-0.30	-0.30	0.47
1997	FSD	14.80	-0.29	-0.29	0.18	303.02	-0.29	-0.29	0.38
1998	FSD	15.24	-0.26	-0.26	0.16	340.35	-0.30	-0.30	0.48
1999	FSD	14.62	-0.45	-0.45	0.21	293.55	-0.45	-0.45	0.51
2000	FSD	13.78	-0.25	-0.25	0.14	285.84	-0.37	-0.37	0.51
2001	FSD	14.62	-0.29	-0.29	0.17	295.95	-0.29	-0.29	0.52
2002	FSD	15.84	-0.33	-0.33	0.36	344.21	-0.41	-0.41	0.77
2003	FSD	13.85	-0.26	-0.26	0.15	301.62	-0.26	-0.26	0.43
2004	FSD	15.42	-0.25	-0.25	0.25	274.34	-0.32	-0.32	0.87
2005	FSD	15.22	-0.22	-0.22	0.31	255.04	-0.27	-0.27	0.58
2006	FSD	15.64	-0.26	-0.26	0.34	375.20	-0.26	-0.26	0.81
2007	FSD	15.40	-0.25	-0.25	0.10	281.80	-0.56	-0.56	0.53
2008	FSD	13.37	-0.34	-0.34	0.11	220.90	-0.46	-0.46	0.47
2009	FSD	13.66	-0.28	-0.28	0.20	297.15	-0.28	-0.28	0.54
2010	FSD	12.28	-0.22	-0.22	0.21	284.13	-0.22	-0.22	0.51
2011	FSD	11.90	-0.39	-0.39	0.22	244.62	-0.42	-0.42	0.59
2012	FSD	12.49	-0.25	-0.25	0.33	216.75	-0.25	-0.25	0.71

5.3 Counterfactual Analysis of Different Wage Groups

In this section, we report the findings of counterfactual analysis for different wage groups. We used the weighted median wage of our sample, \$18.5 per hour, as the cut-off point. Higher wage group consists of workers with wages above the median, and the rest are in the lower wage group.

5.3.1 Counterfactual Analysis of Higher Wage Group

We conducted the two kinds of counterfactual analysis again for the higher wage workers. The findings are reported in Tables 7 & 8. In line with Table 6, Table 8 also indicates

a first-order distributional wage premium of human capital characteristics in favor of the incumbents. But still, among higher paid workers, such an edge is also not statistically significant, neither is the second-order dominance relation significant for any year in sample. We have our most interesting finding in Table 7, which summarizes the wage gap caused by inequality in wage structure for higher paid workers. In many years, we find that the newly hired worker’s wage distribution and the counterfactual wage distribution # 1 are generally unrankable. However, we do find second-order dominance relations in the years of 1997, 2000, 2001, 2003, 2008, 2010 and 2011. More notably, the dominance relations reversed direction. The wage distribution of newly hired workers empirically dominates, in a second-order sense, the counterfactual wage distribution # 1. Although they are largely statistically insignificant, the reverse of the dominance relations, to some degree, confirmed our hypothesis that certain highly paid new workers actually enjoyed a better wage structure than their incumbent counterparts, the so called “new hire premium” in the literature. For workers with a social welfare function in the class U_2 , the counterfactual case that replace new hire’s wage structure with that of incumbent workers, while keeping their characteristics constant, would actually make those new hires worse off.

Table 7: Stochastic Dominance Test Results Counterfactual #1 (Higher Wage Workers)

Year	Observed Rank	$d_{1,max}$	$d_{2,max}$	d	$P(d \leq 0)$	$s_{1,max}$	$s_{2,max}$	s	$P(d \leq 0)$
1996	None	2.09	3.17	2.09	0.00	0.26	40.10	0.26	0.26
1997	SSD	1.85	3.10	1.85	0.10	-0.30	49.34	-0.30	0.65
1998	None	0.80	6.16	0.80	0.06	0.80	118.62	0.80	0.18
1999	None	0.34	6.09	0.34	0.03	0.14	79.75	0.14	0.38
2000	SSD	1.05	3.50	1.05	0.15	-0.65	80.04	-0.65	0.47
2001	SSD	1.38	5.59	1.38	0.00	-0.39	100.11	-0.39	0.51
2002	None	0.23	4.42	0.23	0.07	0.23	118.22	0.23	0.23
2003	SSD	0.46	4.28	0.46	0.00	-0.61	102.91	-0.61	0.46
2004	None	1.72	5.78	1.72	0.00	3.52	30.94	3.52	0.16
2005	None	0.76	4.63	0.76	0.02	0.66	56.92	0.66	0.14
2006	None	2.59	2.61	2.59	0.00	11.49	38.30	11.49	0.23
2007	None	5.66	2.16	2.16	0.02	21.11	0.63	0.63	0.18
2008	SSD	0.44	7.88	0.44	0.03	-0.18	104.73	-0.18	0.59
2009	None	4.27	6.15	4.27	0.02	10.85	121.45	10.85	0.14
2010	SSD	0.33	11.37	0.33	0.00	-0.83	315.47	-0.83	0.82
2011	SSD	2.01	2.83	2.01	0.00	-0.35	18.44	-0.35	0.30
2012	None	4.34	1.83	1.83	0.00	15.58	0.55	0.55	0.13

Table 8: Stochastic Dominance Test Results Counterfactual #2 (Higher Wage Workers)

Year	Observed Rank	$d_{1,max}$	$d_{2,max}$	d	$P(d \leq 0)$	$s_{1,max}$	$s_{2,max}$	s	$P(d \leq 0)$
1996	FSD	14.50	-0.30	-0.30	0.18	303.47	-0.30	-0.30	0.39
1997	FSD	14.80	-0.29	-0.29	0.12	303.02	-0.29	-0.29	0.37
1998	FSD	15.24	-0.26	-0.26	0.12	340.35	-0.30	-0.30	0.41
1999	FSD	14.62	-0.45	-0.45	0.21	293.55	-0.45	-0.45	0.42
2000	FSD	13.78	-0.25	-0.25	0.16	285.84	-0.37	-0.37	0.54
2001	FSD	14.62	-0.29	-0.29	0.19	295.95	-0.29	-0.29	0.42
2002	FSD	15.84	-0.33	-0.33	0.32	344.21	-0.41	-0.41	0.76
2003	FSD	13.85	-0.26	-0.26	0.19	301.62	-0.26	-0.26	0.49
2004	FSD	15.42	-0.25	-0.25	0.32	274.34	-0.32	-0.32	0.81
2005	FSD	15.22	-0.22	-0.22	0.36	255.04	-0.27	-0.27	0.66
2006	FSD	15.64	-0.26	-0.26	0.34	375.20	-0.26	-0.26	0.75
2007	FSD	15.40	-0.25	-0.25	0.12	281.80	-0.56	-0.56	0.41
2008	FSD	13.37	-0.34	-0.34	0.11	220.90	-0.46	-0.46	0.60
2009	FSD	13.66	-0.28	-0.28	0.15	297.15	-0.28	-0.28	0.49
2010	FSD	12.28	-0.22	-0.22	0.15	284.13	-0.22	-0.22	0.45
2011	FSD	11.90	-0.39	-0.39	0.22	244.62	-0.42	-0.42	0.59
2012	FSD	12.49	-0.25	-0.25	0.20	216.75	-0.25	-0.25	0.60

5.3.2 Counterfactual Analysis of Lower Wage Group

The results of counterfactual analysis for the lower paid group are reported in Tables 9 & 10. Table 10 shows similar results as Table 6, indicating better human capital characteristics among incumbent workers with hourly wage lower than \$18.5.

Table 9 reports the stochastic dominance test results between the original wage distribution of the new hires and the counterfactual wage distribution #1 among lower paid group. We have some interesting findings here. In the years of 1996, 1997, 2000-2003 and 2005-2009, the counterfactual wage distribution #1 empirically dominates, in a first-order sense, the wage distribution of newly hired workers. In the years of 1998, 2004, 2010 and 2011, the counterfactual wage distribution #1 empirically dominates, in a second-order sense, the wage distribution of newly hired workers. First-order dominance relation is largely insignificant, but in 1997 and 2008, the second-order dominance relations are statistically significant, with p-values less than 0.1. The findings indicate that for lower wage workers, the counterfactual wage distribution #1 are preferred compared to the actual new hire wage distribution for workers with a social welfare function in the class of U_2 in both years. The significant dominance relation in 2008, provides a strong evidence that during the recent great recession year, lower wage new hired workers suffer from a much worse pay structure than that of the incumbents. It is an indicator showing that the external labor

Table 9: Stochastic Dominance Test Results for Lower Wage Workers, Counterfactual #1

Year	Observed Rank	$d_{1,max}$	$d_{2,max}$	d	$P(d \leq 0)$	$s_{1,max}$	$s_{2,max}$	s	$P(d \leq 0)$
1996	FSD	13.34	-0.13	-0.13	0.15	365.28	-0.22	-0.22	0.84
1997	FSD	18.51	-0.22	-0.22	0.83	544.61	-0.26	-0.26	0.92
1998	SSD	18.00	0.47	0.47	0.04	402.38	-0.20	-0.20	0.70
1999	None	15.13	0.19	0.19	0.13	388.87	0.64	0.64	0.21
2000	FSD	13.52	-0.17	-0.17	0.58	394.86	-0.23	-0.23	0.71
2001	FSD	10.85	-0.23	-0.23	0.55	287.80	-0.25	-0.25	0.84
2002	FSD	11.11	-0.26	-0.26	0.46	327.00	-0.29	-0.29	0.81
2003	FSD	10.37	-0.01	-0.01	0.29	293.57	-0.20	-0.20	0.68
2004	SSD	8.33	0.90	0.90	0.04	198.47	-0.23	-0.23	0.31
2005	FSD	8.71	-0.26	-0.26	0.11	202.16	-0.26	-0.26	0.40
2006	FSD	12.60	-0.31	-0.31	0.38	243.86	-0.52	-0.52	0.84
2007	FSD	10.71	-0.15	-0.15	0.17	222.28	-0.24	-0.24	0.36
2008	FSD	10.11	-0.03	-0.03	0.35	246.93	-0.17	-0.17	0.90
2009	FSD	10.45	-0.01	-0.01	0.34	268.62	-0.19	-0.19	0.71
2010	SSD	6.42	0.03	0.03	0.15	200.86	-0.21	-0.21	0.72
2011	SSD	6.46	1.14	1.14	0.01	148.40	-0.19	-0.19	0.39
2012	None	8.91	0.64	0.64	0.01	177.41	0.77	0.77	0.28

market deteriorates much more than the internal labor market during the recent recession.

Table 10: Stochastic Dominance Test Results for Lower Wage Workers, Counterfactual #2

Year	Observed Rank	$d_{1,max}$	$d_{2,max}$	d	$P(d \leq 0)$	$s_{1,max}$	$s_{2,max}$	s	$P(d \leq 0)$
1996	FSD	14.50	-0.30	-0.30	0.11	303.47	-0.30	-0.30	0.46
1997	FSD	14.80	-0.29	-0.29	0.10	303.02	-0.29	-0.29	0.36
1998	FSD	15.24	-0.26	-0.26	0.22	340.35	-0.30	-0.30	0.53
1999	FSD	14.62	-0.45	-0.45	0.20	293.55	-0.45	-0.45	0.46
2000	FSD	13.78	-0.25	-0.25	0.13	285.84	-0.37	-0.37	0.46
2001	FSD	14.62	-0.29	-0.29	0.22	295.95	-0.29	-0.29	0.62
2002	FSD	15.84	-0.33	-0.33	0.31	344.21	-0.41	-0.41	0.76
2003	FSD	13.85	-0.26	-0.26	0.12	301.62	-0.26	-0.26	0.48
2004	FSD	15.42	-0.25	-0.25	0.31	274.34	-0.32	-0.32	0.85
2005	FSD	15.22	-0.22	-0.22	0.30	255.04	-0.27	-0.27	0.65
2006	FSD	15.64	-0.26	-0.26	0.46	375.20	-0.26	-0.26	0.77
2007	FSD	15.40	-0.25	-0.25	0.11	281.80	-0.56	-0.56	0.41
2008	FSD	13.37	-0.34	-0.34	0.09	220.90	-0.46	-0.46	0.46
2009	FSD	13.66	-0.28	-0.28	0.19	297.15	-0.28	-0.28	0.55
2010	FSD	12.28	-0.22	-0.22	0.19	284.13	-0.22	-0.22	0.54
2011	FSD	11.90	-0.39	-0.39	0.17	244.62	-0.42	-0.42	0.65
2012	FSD	12.49	-0.25	-0.25	0.15	216.75	-0.25	-0.25	0.62

6 Conclusion

This paper employs a distribution based entropy metric to measure the wage differentials between incumbent and newly hired employees. The entropy measure incorporates the differences at the entire distribution level and thus gives a better picture on wage comparison. We also use stochastic dominance tests to rank those wage distributions based on social welfare. We find that the incumbent workers are generally paid better than the newly hired worker in any year from 1996 to 2012. Further counterfactual analysis shows that the wage gap could be attributed to both the inequality in wage structures and the differences in human capital characteristics, depending on a worker's wage level. For highly paid new workers, the wage gap mainly comes from the differences in human capital characteristics and those new hires tend to enjoy a better wage structure than the incumbents in certain years. For lower paid new workers, the wage differential comes from both gap in human capital characteristics and the inequality in wage structure. Especially in the recent recession year 2008, those lower wage new hires suffer more from the significantly worse wage structure than that of the incumbents.

References

- ALBRECHT, J., A. BJÖRKLUND, AND S. VROMAN (2003): “Is there a glass ceiling in Sweden?” *Journal of Labor Economics*, 21, 145–177.
- BAKER, G., M. GIBBS, AND B. HOLMSTROM (1994): “The internal economics of the firm: Evidence from personnel data,” *The Quarterly Journal of Economics*, 109, 881–919.
- BARSKY, R., J. BOUND, K. K. CHARLES, AND J. P. LUPTON (2002): “Accounting for the black–white wealth gap: a nonparametric approach,” *Journal of the American Statistical Association*, 97, 663–673.
- BLAU, F. AND L. KAHN (2006): “The US Gender Pay Gap in the 1990s: Slowing Convergence,” *Industrial and Labor Relations Review*, 45–66.
- BLINDER, A. S. (1973): “Wage Discrimination: Reduced Form and Structural Estimates,” *Journal of Human Resources*, 8, 436–455.
- BOURGUIGNON, F. (1979): “Decomposable Income Inequality Measures,” *Econometrica*, 47, 901–20.
- DI NARDO, J., N. M. FORTIN, AND T. LEMIEUX (1996): “Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach,” *Econometrica*, 64, 1001–1044.
- DOERINGER, P. AND M. PIORE (1985): *Internal labor markets and manpower analysis*, ME Sharpe (Armonk, NY).
- FIRPO, S. (2007): “Efficient semiparametric estimation of quantile treatment effects,” *Econometrica*, 75, 259–276.
- FIRPO, S., N. FORTIN, AND T. LEMIEUX (2007): “Decomposing wage distributions using recentered influence function regressions,” Working paper.
- GRANGER, C., E. MAASOUMI, AND J. RACINE (2004): “A dependence metric for possibly nonlinear processes,” *Journal of Time Series Analysis*, 25, 649–669.
- KAMPKÖTTER, P. AND D. SLIWKA (2011): “Wage premia for newly hired employees: theory and evidence,” .
- KLINE, P. (2011): “Oaxaca-Blinder as a reweighting estimator,” *American Economic Review*, 101, 532–37.

- LINTON, O., E. MAASOUMI, AND Y. WHANG (2005): “Consistent testing for stochastic dominance under general sampling schemes,” *The Review of Economic Studies*, 72, 735–765.
- MAASOUMI, E. (1986): “The Measurement and Decomposition of Multi-Dimensional Inequality,” *Econometrica*, 54, 991–997.
- MAASOUMI, E. AND A. HESHMATI (2000): “Stochastic dominance amongst Swedish income distributions,” *Econometric Reviews*, 19, 287–320.
- MAASOUMI, E. AND J. RACINE (2002): “Entropy and predictability of stock market returns,” *Journal of Econometrics*, 107, 291–312.
- MADRIAN, B. C. AND L. J. LEFGREN (1999): “A Note on Longitudinally Matching Current Population Survey (CPS) Respondents,” NBER Technical Working Papers 0247, National Bureau of Economic Research, Inc.
- MASSOUMI, E. AND L. WANG (2012): “The Gender Earnings Gap: Measurement and Analysis,” Working paper.
- OAXACA, R. (1973): “Male-female wage differentials in urban labor markets,” *International economic review*, 14, 693–709.
- OREOPOULOS, P., T. VON WACHTER, AND A. HEISZ (2006): “The Short- and Long-Term Career Effects of Graduating in a Recession: Hysteresis and Heterogeneity in the Market for College Graduates,” Working Paper 12159, National Bureau of Economic Research.
- SHORROCKS, A. F. (1978): “The measurement of mobility,” *Econometrica: Journal of the Econometric Society*, 1013–1024.