The Gender Earnings Gap: Measurement and Analysis

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Abstract

This paper presents a set of complementary tools for measurement and analysis of the gender gap that move beyond the simple moment-based comparison of the earnings distributions. In particular, we propose a new measure of the gender gap based on the the distance between two *whole* distributions, instead of their specific parts. We also introduce tests based on stochastic dominance to allow for robust welfare comparisons of the earnings distributions between men and women. Using the Current Population Survey data, we first construct a new series on the gender gap from 1976 to 2011 in the United States. We find that traditional moment-based measures severely underestimate the declining trend of the gender gap during this period. More important, these traditional measures do not necessarily reflect the cyclicality of the gender differentials in earnings distributions, and thus may even lead to a false conclusion about how labor market conditions are related to the gender gap at the aggregate level. Second, we find that stochastic dominance (or a clear ranking of the earnings distributions) is rare, and that instances in which we do find stochastic dominance appear to be disproportionately concentrated in the pre-welfare reform period and related to economic recessions. Finally, our counterfactual analysis show that in most cases neither changing earnings structure nor changing human capital characteristics would necessarily improve women's well-being uniformly in the society.

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1. Introduction

Studying the gender gap (i.e. earnings differences between men and women) is an important undertaking, as it gets at the core of social sciences to understand inequality in the society and helps shed light on potential means to reduce it. Policymakers and economists are generally interested in two questions: (1) How large is the gender gap in the society? (2) How do women fare compared to men in the labor market? The answer to the first question entails measurement of the differences in the earnings distributions of men and women, and the answer to the second question involves ranking of these distributions.

Conventional wisdom about the gender gap is that women fare worse than men do in the labor market. Often cited to support this view is examination of the earnings differentials between representative men and women, for example, the earnings differences between average men and women or the earnings differences between median men and women (e.g. Polachek, 2006; Blau and Kahn, 2006). The magnitude of the differences tells us which group fares better in the labor market, and the size how severe the situation is. Although useful, it is, however, not very clear why the differences at the "representative" part of the earnings distribution (mean or median) necessarily summarize the differences between the earnings distributions of men and women – *the gender gap in the whole society*. Researchers are increasingly aware of this issue, and, as a result, the differences at other parts of the earnings distributions (e.g. 90th percentile) are also reported in recent years. These different summary statistics greatly improve our understanding of the extent of the gender gap.

Yet, it is not complete. As in many empirical studies, economists and policymakers are often interested in one number but not "a multidimensional estimate" (Frolich, 2007). When multiple measures exist and differ in terms of magnitudes and signs, it is difficult to summarize the information in the society well. And this problem would be even more acute when examining the time trend of the gender gap. The timing of temporal deviations from the long-run trend could vary across different measures, which could in turn lead to a false sense of the impact of business cycles on the gender gap in the society. Furthermore, in this case, any ranking of the earnings distributions of men and women would also involve different weighting schemes representing different personal values, which inevitably lead to different conclusions.

To make some of our points more concrete, consider the following simple numerical examples for a society with only two men (Male A and Male B) and two women (Female A and Female B).

Example 1 The difference in earnings between Female A and Male A is $-\$200$, and that between Female B and Male B is $-\$500$. A typical measure, the average difference, suggests that the gender gap is $-\$350$. However, average persons do not even exist in the society. Use of either $-\$200$ or $-\$500$ ignores the other half of the society and consequently does not summarize the situation well. In this example, all the measures are negative, impling that men fare better than do women in the labor market.

Example 2 The difference in earnings between Female A and Male A is $-\$200$, but that between Female B and Male B is now \$200. The average difference suggests that the gender gap is \$0! Again, average persons do not even exist in the society, and it suggests there is no gender gap at all. As with the previous example, use of either $-\$200$ or \$200 as a measure of the gender gap also ignores the rest of the society. Compared to Example 1, this example is more complicated. Since these differences differ in signs, they suggest different rankings of the earnings distributions between men and women. Any conclusions would be based on an arbitrary weighting scheme. For example, the conclusion that women perform worse in the labor market implies that more weights are placed on the difference between Female A's and Male A's earnings. Left untold is why this type of weighting scheme is justified and what type of social welfare function it represents to make this conclusion possible.

Example 3 Consider another example similar to the second one but with more information on actual earnings for each individual. Female A earns $\$55,000$ and Male A

$54,500. Female B earns \$800 and Male B \$1,000. The difference in earnings between Female A and Male A is \$500, and that between Female B and Male B is −\$200. This example represents a society where rich women earn more than rich men, while poor women earn less than poor men. The first pair resembles the difference at the upper tail of the earnings distribution, whereas the second the difference at the lower tail – both commonly used in the literature. In this example, we, again, cannot find a particular measure that summarizes the gender gap without ignoring the rest of the society. More important, we cannot rank the earnings distributions of men and women. Given the additional information on each person's earnings, some individuals who are more adverse to inequality may emphasize the difference in lower tail, concluding existence of the gender gap in favor of men. However, this type of "preference" is usually not explicitly stated in practice. And clearly, the conclusion cannot necessarily be generalized for individuals possessing different welfare functions.

These three examples highlight the conceptual difficulties in measuring the gender gap in the whole society and in ranking the earnings distributions. To circumvent these problems, this paper presents a set of complementary tools that move beyond the simple moment-based comparison of the earnings distributions. Specifically, we first propose a distributional measure of the gender gap based on the normalized Bhattacharay-Matusita-Hellinger entropy measure proposed by Granger et al. (2004). One important feature, among others, of this measure is its ability to summarizes the distance between two *whole* distributions, instead of simple differences at different *parts* of the distributions. Second, we employ stochastic dominance (SD) tests to rank the earnings distributions. The SD tests have been widely used to analyze poverty issues but less so to analyze the gender earnings gap. The advantage of the SD approach is its explicit welfare underpinning, utilization of the entire earnings distributions, and ability to yield uniform rankings of distributions that are robust across a wide class of welfare functions. Inferring a dominance relation implies that comparisons based on multiple measures are unnecessary. Moreover, the inability to infer a dominance relation is equally informative, indicating that any ranking must be based on a particular weighting scheme or a specific welfare function. The conclusion is highly subjective and may not be informative for policy-making.

Our arguments here can be similarly applied to counterfactual analysis of interest. Policy-makers and economists are often interested in certain policies to bridge the gap and improve the well-being of women. These policies can be loosely classified into two groups: (1) policies aim at changing women's pay structure and (2) policies aimed at changing their observable characteristics that affect their earnings. These types of policies are related to two major reasons that most think why there exist differences in earnings between women and men: differences in wage structure and differences in human capital characteristics; the former is often considered to be related to "discrimination". Regardless of which type of policy to be implemented, assessment is in order of the changes in the potential earnings among women resulted from the policy implemented. To evaluate a policy, we need to compare the original earnings distribution with the potential earnings distribution resulted from a policy. In most cases, there would be both "losers" and "winners" as a result of a policy change. Consequently, we again face the challenges posed above. Differences in different parts of the earnings distribution, again, cannot necessarily summarize the change in the whole society. And when the magnitudes and signs of these differences differ across the distribution – meaning that there are "losers" and "winners" – the conclusions again depend on personal values or welfare criteria. Thus, the approaches proposed in this paper naturally fits into this type of counterfactual analysis.

To illustrate our proposed approaches, we utilize the Current Population Survey (CPS) data 1976 - 2011 in the U.S. for our empirical analysis. We reach several conclusions. First, we find that traditional moment-based measures severely underestimate the declining trend of the gender gap in the U.S. In particular, our measure implies the gender gap narrowed at average annual rate of about 11% during the period 1976-2011, while the annual rate implied by the gender difference at the median is only 5.2% during the same period, the largest among all conventional measures. Moreover, even though all measures show a consistently declining trend of the gender gap, the timing of temporal deviations from the long-run varies across different measures, which in turn leads to a false sense of the impact of business cycles on the gender gap in the society. Second, we find that stochastic dominance is not common, implying that we generally cannot rank the earnings distributions of men and women. And even in those cases where we do find dominance relations, the relation is only second-order and statistically insignificant. In other words, we cannot reach a conclusion that men do better than do women unless we allow for a narrower class of social welfare functions (that are increasing in earnings but averse to inequality). Moreover, the SD relations are found disproportionately in the pre-1994 period, before welfare reforms started. In the post-1994 period, all the SD relations appear to be related to economic recessions. We argue that even though effective in promoting women's well-being during usual economic conditions, welfare reforms do not necessarily make women less vulnerable to worsened economic conditions. Third, even though we do not find many dominance relations using the full sample, we do find more cases of "restricted dominance" when extremely poor individuals are excluded in our analysis. And these dominance relations are, again, concentrated disproportionately in the pre-1994 period.

Finally, combining the methods proposed here and the recent development in identification of counterfactual analysis, we further compare the female earnings distribution with two female counterfactual earnings distributions (the earnings that women would earn under the earnings structure of men and the earnings that women would earn should they have men's characteristics). The former captures *structural effects* and the latter *composition effects*. We find that structural effects are generally more important than composition effects. However, the importance of structural effects has declined over time, while that of composition effects has increased. We in general fail to find many SD results, and our SD results of lack of dominance relations in many cases suggest that neither changing earnings structure nor changing human capital characteristics would necessarily improve women's well-being uniformly in the society.

While in this paper we focus on measurement and analysis of the gender earnings gap, we believe that our research could be further extended along several dimensions. First, our approaches could be readily adapted to measure and analyze other types of the earnings differentials between two groups, typically advantageous group v.s. disadvantageous group (e.g. white v.s. black – the racial gap). Second, in this paper we focus on the earnings as the only attribute of welfare. However, researchers have long recognized that welfare involves not only earnings but other attributes such as health, and, as a result, a growing literature has developed investigating multi-dimensional welfare measures that take into account earnings and other factors jointly (e.g. Wu et al., 2008). Our approaches are defined over the space of *distributions* and can be applied to univariate and multivariate contexts. Thus, unlike conventional measures focusing on univariate variables, our approaches are also promising in measuring and analyzing the gender gap in the multi-dimensional welfare framework. Finally, aggregate time series of our distributional measure of the gender gap, once obtained, can be used for further empirical analysis. For example, Biddle and Hamermesh (2011) has noted that little is known about how wage differentials vary with the extent of labor market conditions. Our measure can directly be used for this purpose (in the spirit of Ashenfelter (1970)) to examine the aggregate relationship between the gender gap and the aggregate unemployment rate.

The rest of the paper is organized as follows. Section 2 presents the empirical methods employed; Section 3 describes the data; Section 4 discusses the results, and Section 5 concludes.

2. Empirical Methodology

2.1. Basic Notations

To begin, let $\ln(w^f)$ and $\ln(w^m)$ denote the log of earnings for females and males, respectively. We observe a random sample of $N = N_0 + N_1$ individuals. $\{\ln(w^f)\}_{i=1}^{N_1}$ is a vector of N_1 observations of $\ln(w^f)$ (denoted by $D_i = 1$); similarly, $\{\ln(w_i^m)\}_{i=1}^{N_0}$ is a vector of N_0 observations of $\ln(w^m)$ (denoted by $D_i = 0$). Let $F_1(y) \equiv Pr[\ln(w^f) \leq y]$ represent the cumulative density function (CDF) of $\ln(w^f)$ (i.e. the log of earnings for females) and $f_1(y)$ the corresponding probability density function (PDF); $F_0(y)$ and $f_0(y)$ are similarly defined for $\ln(w^m)$ (i.e. the log of earnings for males). Individual earnings are determined by both observable characteristics X_i and unobservable characteristics ϵ_i via unknown wage structure functions,

$$\ln(w_i^d) = g_d(X_i^d, \epsilon_i^d) \quad d = m, f$$

This specification implies that the gender gap is from three sources: (1) differences in the distributions of observable human capital characteristics X_i^d (e.g. years of schooling); (2) differences in the distributions unobservable human capital characteristics ϵ_i^d (e.g. innate ability); (3) differences in the wage structures, $g_d(\cdot)$. Note that these wage functions are not restrictive and allow for complicated interactions among X_i^d and ϵ_i^d.

2.2. A Distributional Measure of the Gender Earnings Gap

Usually, the gender gap is defined as the difference in certain parts (or functionals) of the earnings distributions between males and females. For example, average gender gap is the difference in the means of the earnings distribution between men and women ($\mathbb{E}[\ln(w_i^m)] - \mathbb{E}[\ln(w_i^f)]$) (where the mean is the first moment of the earnings distribution). The gender gap at a p^{th} quantile is $\ln(w_i^m)^p - \ln(w_i^f)^p$, where the p^{th} quantile of F_0 (the CDF for women's wage distribution) is given by the smallest value $\ln(w_i^f)^p$ such that $F_1(\ln(w_i^f)^p) = p$; $\ln(w_i^m)^p$ is similarly defined for F_1 (the CDF for men's wage distribution). Even though these measures are all functionals of the wages distributions, none of them is able to summarize the information in the *whole* distribution. This problem is particularly acute when the measures differ in terms of magnitudes and sizes across different measures used. Hence, needed is a distributional measure of the gender gap, or a measure of the distances in the earnings distributions between females and males.

Several commonly used information-based entropy measures such as Shannon-Kullback-Leibler are available to measure the information at the distributional level. However, Shannon's entropy measure as well as almost all other entropy measures are not *metric*; these measures violate the triangularity rule and hence cannot be used as a measure of *distance*.

To this end, we use a *metric* entropy measure S_ρ proposed in Granger et al. (2004), which is a normalization of the Bhattacharya-Matusita-Hellinger measure of distance. It is given by

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

This measure satisfies several desirable properties: (1) it is well defined for both continuous and discrete variables;[1] (2) it is normalized to zero if Y_1 and Y_0 are equal, and lies between 0 and 1, (3) it is a metric and hence a true measure of *distance*, (4) it is invariant under continuous and strictly increasing transformation $h(\cdot)$ on the underlying variables.[2] Recall that following the literature we utilize the log of earnings as the variable of main interest. Since the log is a strictly increasing function, our measure of the gender gap is the same, whether we use the raw wages or the log of it. Moreover, entropies are defined over the space of *distributions* and are consequently "dimension-less" as it applies to univariate and multivariate contexts. Economists have been increasingly aware of the fact that evaluation of individual well-being is inevitably a multi-attribute exercise (Lugo and Maasoumi, 2008). This feature may become very useful when we consider the *multidimensional* gender gap measure to incorporate attributes other than wages.

Following Granger et al. (2004) and Maasoumi and Racine (2002), we consider a kernel-based implementation of (1) (The computer code **-srho-** written by the authors in S-

[1]Although (1) presumes that the variables are continuous, one can easily adapt this measure to the case of discrete variables, $S_\rho = \frac{1}{2}\sum(p_1^{\frac{1}{2}} - p_0^{\frac{1}{2}})^2$ where p_1 (p_0) is the marginal probability of the random variable Y_1 (Y_0). This generalization allows us to measure the differences in a broader set of outcomes between groups at the distributional level.

[2]Integrated squared norm ($L2$) also shares many of these properties, but it is not normalized and is not invariant to transformations. And it is also thought to be more sensitive "inliers and outliers' (Hart, 1997).

tata is also available upon request). In our illustrative example below, we use Gaussian kernels and a more robust version of the "normal reference rule-of-thumb" bandwidth ($= 1.06 \min(\sigma_d, \frac{IQR^d}{1.349}) * n^{-1/5}$, where $\sigma_d, d = m, f$ is the sample standard deviation of $\{\ln(w_i^d)\}_{i=1}^{N_d}$; IRQ^d is the interquartile range of the sample d.). Interested readers are referred to Li and Racine (2007) for more sophisticated bandwidth selection procedures. Integrals are numerically approximated by the integrals of the fitted cubic splines of the data, which "give superior results for most smooth functions" (StataCorp, 2009). The asymptotic distribution of the feasible measure has been derived by Skaug and Tjostheim (1996) and Granger et al. (2004). However, these asymptotic approximations are well known to perform very poorly in almost every case examined. As a result, in the analysis below, we instead employ bootstrap re-sampling procedure based on 299 replications to obtain critical values of hypothesis testing of $H_0 : S_\rho = 0$.

Our entropy measure of gender gap gives us information on the distances between two wage distributions. However, it does not directly tell us which distribution is "better" and under what conditions it is. Below, we explicitly introduce these concepts to rank/compare two distributions.

2.3. Stochastic Dominance

We employ tests for SD to enable welfare comparisons of the earnings distributions between females and males ($\ln(w^f)$ and $\ln(w^m)$). The SD approach explicitly state for which class of social welfare functions rankings of the earnings distributions are possible. In this paper, we consider two classes of social welfare functions that are commonly used in the literature. Let U_1 denote the class of all (increasing) von Neumann-Morgenstern type of social welfare functions u such that welfare is increasing in wages (i.e. $u' \geq 0$), and U_2 the class of social welfare functions in U_1 such that $u'' \leq 0$ (i.e. concavity). Concavity implies an aversion to higher dispersion (or inequality) of wages across individuals. Note, here, that we abstract from the issue of multi-dimensional welfare and focus on the social welfare function of only earnings. We are interested in the following scenarios:

Case 1 (First Order Dominance):

Male Earnings ($\ln(w^m)$) First Order Stochastically Dominates Female Earnings ($\ln(w^m)$) (denoted $\ln(w^m)$ FSD $\ln(w^m)$) *if and only if*

1. $\mathbb{E}[u(\ln(w^m))] \geq \mathbb{E}[u(\ln(w^f))]$ 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):

Male Earnings ($\ln(w^m)$) Second Order Stochastically Dominates Female Earnings ($\ln(w^f)$) (denoted $\ln(w^m)$ SSD $\ln(w^f)$) *if and only if*

1. $\mathbb{E}[u(\ln(w^m))] \geq \mathbb{E}[u(\ln(w^f))]$ 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.

These two cases imply rankings of the earnings distributions under different conditions. Specifically, if the case 1 holds ($\ln(w^m)$ FSD $\ln(w^f)$), then the earnings distribution among men is "better" than that among women for all policymakers with increasing utility functions in the class U_1 (with strict inequality holding for some welfare function(s) in the class), since the expected social welfare from $\ln(w^m)$ is larger or equal to that from $\ln(w^f)$. Note that $\ln(w^m)$ FSD $\ln(w^f)$ implies that the average male wages are greater than the average female wages. "However, a ranking of the average wages does not imply that one FSD the other; rather, the entire distribution matters" (Mas-Colell et al., 1995, p.196). Similarly, if the case 2 holds ($\ln(w^m)$ SSD $\ln(w^f)$), then the earnings distribution of males is "better" than that of females for those with increasing and concave welfare functions in the class U_2 (with strict inequality holding for some utility function(s) in the class). Note that FSD implies SSD. One immediate advantage of our proposed approach is that our conclusions do not depend on any specific functions or weights assigned to the distributions. This approach is thus able to yield uniform rankings of distributions that are robust across a wide class of welfare functions, rendering comparisons based on specific indices unnecessary.

In this paper, we employ stochastic dominance tests based on a generalized Kolmogorov-Smirnov test discussed in Linton et al. (2005) and Maasoumi and Heshmati (2000). The Kolmogorov-Smirnov test statistics for FSD and SSD are given by

$$d = \sqrt{\frac{N_0 N_1}{N_0 + N_1}} \min \sup [F_1(y) - F_0(y)] \tag{2}$$

$$s = \sqrt{\frac{N_0 N_1}{N_0 + N_1}} \min \sup \int_{-\infty}^{y} [F_1(t) - F_0(t)] dt \tag{3}$$

Practical implementation of these test statistics is based on the sample counterparts of d and s by replacing CDFs with empirical ones; the empirical CDFs are given by $\widehat{F_1(y)} = \frac{1}{N_1} \sum_{i=1}^{N_1} I(\ln(w_i^f) \leq y)$, where $I(\cdot)$ is an indicator function; $\widehat{F_0(y)}$ is similarly defined. The underlying distribution of the test statistics are generally unknown and depend on the data. Following the literature (e.g. Maasoumi and Heshmati, 2000; Millimet and Wang, 2006), we use simple bootstrap technique based on 299 replications to obtain the empirical distribution of the test statistics. If the probability of d lies in the non-positive interval (i.e. $Pr[d \leq 0]$ is large, say .90 or higher, and $\widehat{d} \leq 0$, we can infer FSD to a desirable degree of statistical confidence. We can infer SSD based on s and $Pr[s \leq 0]$ in a similar fashion. All technical details are presented in Appendix 1.

2.4. Counterfactual Distributions

As mentioned above, we are often interested in answering two types of counterfactual situations: First, what if we change the wage structure of women to the wage structure of men, holding the distribution of women's human capital characteristics constant? Second, what if we change the distribution of women's human capital characteristics to that of men's, holding the wage structure unchanged? Will these counterfactual distributions be different from the original one? Will these changes necessarily improve women's earnings distribution?

Our proposed approaches can be readily applied to answer these counterfactual questions by measuring the distances between the female earnings distribution and the counterfactual distribution and ranking them. The key is how we can identify the counterfactual distributions of interest. To make it more concrete, we want to identify the distributions of the following counterfactual outcomes:

$$\ln(w_i^{c1}) = g_0(X_{i1}, \epsilon_{i1}) \quad \text{(Counterfactual Outcome \#1)} \tag{4}$$

$$\ln(w_i^{c2}) = g_1(X_{i0}, \epsilon_{i0}) \quad \text{(Counterfactual Outcome \#2)} \tag{5}$$

F_{c1} (f_{c1}) represents the corresponding CDF (PDF) of the counterfactual outcome $\ln(w_i^{c1})$. F_{c2} (f_{c2}) represents the corresponding CDF (PDF) of the counterfactual outcome $\ln(w_i^{c2})$. Notice that the differences in the distributions of F_{c1} and F_1 ($\ln(w_i^{c1})$ v.s. $\ln(w_i^f)$) come solely from differences in wage structures; the comparisons of these two distributions thus provide insight into potential *discrimination*. On the other hand, the differences in the distributions of F_{c1} and F_1 ($\ln(w_i^{c2})$ v.s. $\ln(w_i^f)$) come solely from differences in the distribution of human capital characteristics; the comparisons thus provide some insight into the gender gap due to *productivity* differences across gender.

As shown Firpo (2007, Lemma 1), under the following assumptions:

[A1.] Unconfoundedness/Ignorability: Let (D, X, ϵ) have a joint distribution. For all x, ϵ is independent of D conditional on $X = x$.

[A2.] Common Support: For all x, $0 < p(x) = \Pr[D = 1|X = x] < 1$.

The counterfactual outcome CDF of $\ln(w_i^{c1})$ is identified and $F_{c1} = \mathbb{E}[\omega_{c1}(D, X) \cdot I[(\ln(w_i) \leq y)]$, where $\omega_{c1}(D, X) = (\frac{p(x)}{1-p(x)}) \cdot (\frac{1-D}{p})$. The counterfactual outcome CDF of $\ln(w_i^{c2})$, F_{c2}, is similarly identified. In practice, $p(x)$ is estimated. Both assumptions (A1) and (A2) are commonly used in the literature. Assumption (A1) implies here that given the values of observable human capital characteristics X, the distribution of unobservable human capital characteristics such as ability is independent of gender. Assumption (A2) rules out the possibilities that a particular value x belongs to either male or female and that the set of wage determinants, (X, ϵ) differ across gender. Interested readers are referred to e.g. Fortin et al. (2011) for detailed explanations of these two assumptions. Once we identify the counterfactual distributions of interest, we can then perform our counterfactual analysis using the approaches discussed above.

3. Data

To perform our analysis, we use data from the 1976-2011 March Current Population Survey (CPS) (available at `http://cps.ipums.org`, King et al., 2010). The March CPS is a large nationally representative household data that contain detailed information on labor market outcomes such as earnings and other characteristics needed for our counterfactual analysis. It thus has been widely used in the literature to study the gender gap (e.g. Waldfogel and Mayer, 2000). We begin at 1976 since it was the first year that information on weeks worked and hours worked are available in the March CPS. We restrict our sample to individuals aged between 18 and 64 who work only for wages and salary. To ensure that our sample includes only those workers with stronger attachment to the labor market, we include only those who worked for more than 20 weeks (inclusive) in the previous year. Moreover, we exclude part-time workers who worked less than 35 hours per week in the previous year.

Following the literature (e.g. Blau and Kahn, 1997), we use the log of hourly wages, measured by an individual's wage and salary income for the previous year divided by the number of weeks worked and hours worked per week. The differences in the distributions of log hourly wages between men and women are our measures of the gender gap. The differences in a specific part of the distribution can be interpreted as percentage differences. Note, however, that our distributional measure of the gender gap and SD tests are invariant to increasing monotonic transformation, while conventional measures of the gender gap are.

In our counterfactual analysis, we include age, age squared, education (four education groups: Below high school, High School, 1-3 years of College, and College and Above), current marital status (1 if non-married and zero otherwise), race (1 if non-white and zero otherwise), and region (northeast, midwest, south, and west). We also include occupations which are divided into three categories: high-skill (managerial and professional specialty occupations); medium-skill (technical, sales, and administrative support occupations); and low-skill(other occupations such as helpers, construction, and extractive occupations).

4. Results

4.1. Baseline Analysis

4.1.1. Trend of the Gender Gap 1976 - 2011

Table (1) reports various measures of the gender earnings gap. Column (1) displays our distributional measure of the gender gap S_ρ. Recall that, S_ρ is normalized, taking on values in $[0, 1]$, and to facilitate the presentation, the results reported are the original values $\times 100$ throughout the paper. The critical values based on 299 replications are reported in Table (A2), columns (1)-(3). Columns (2) and (7) in Table (1) display the gender gap measured as difference at the selected percentiles of the earnings distribution between men and women (mean, 10th, 25th, 50th, 75th and 90th) that are commonly used in the literature.

We first notice that all measures imply that there exist substantial earnings differentials between men and women across years. In particular, S_ρ is statistically significantly different from zero (it is larger than critical values calculated at 99th percentiles of the bootstrapped distribution of S_ρ in all cases). Furthermore, examination of the differences at the selected percentiles of the earnings distribution between men and women are consistently positive, suggesting that men earn more than women do. However, the implied size of the gender earnings differentials in the economy vary with the conventional measures used. For example, in 1976, the gender gap measure at the 10th percentile indicates the gap is about 37 percentage points, while the measure at the 90th percentile implies that it is more than 50 percentage points. The difference is as large as 13 percentage points. The differences at other parts of the earnings distribution indicate the gender gap is between 45 and 47 percentage points. Even though consistently suggesting the existence of the gender gap, none of the conventional measures at a specific part of the earnings distribution seems to accurately summarize the gender gap in the rest of the distribution.

This may not necessarily be a problem in the cross-sectional setting. It, however, does drastically mask the long-run trend in the gender gap. Comparing the measures of the gender gap from 1976 to those from 2011, we clearly see a decrease in the difference between the earnings distributions of men and women over the past four decades, regardless of which measure is used. However, the decrease is not monotonic over time, and the timing of temporal deviations from the long-run trend dramatically varies across different measures used. To ease the presentation, we report the patterns of changes in different measures in Table (A1). The cells with "I" highlighted in green are the years when the measure increased, while the cells with "D" highlighted in light grey are the years when the measure decreased. As we can clearly see, the conventional measures of the gender gap generally do not move in the same direction together, except in few years (1980, 1984, 1988, 1990, 1997, and 2004). For example, the gender gap at the median increased in 1977, while the gender gap at other selected parts of the earnings distributions between men and women decreased. As a result, it is not clear why any of the conventional measures are representative of the rest of the earnings distribution and informative of the general trend of the gap gap in the society. On the other hand, our distributional measure of the gender gap, S_ρ, takes into the changes in all parts of the distributions, thereby providing a more complete picture of the trend in the society. An advantage of our measure is that it does not place all weights on a particular part of the distribution, and the weights vary over time. For example, S_ρ indicates the gender gap in a society decreased in 1977, which is consistent with the decrease implied by the measure at the all parts but 90th percentile; S_ρ indicates the gender gap in the society increased in 1999, which is consistent with the increase in the gender gap measured at the 10th and 75th percentiles. Our measure becomes particularly useful when the commonly used measures disagree with each other, especially during economic downturns. For example, in 2009 (the current recession), the gender gap implied by the mean increased, while that by the median decreased. This conflicting result could lead to different conclusions about the cyclicality of the gender gap in the society. Our measures summarizes the information that a measure at a specific part of the distribution misses. In this particular case, our measure suggests that the gender gap indeed increased (possibly due to worsened economic conditions), in agreement with the conclusion implied by the mean. Prior to continuing, one interesting finding is worth mentioning. It seems that the gender gap at the 10th percentile fluctuates more around the trend over time, compared to the measures at other parts of the distribution; the gender gap at the 90th percentile, although fluctuating sometimes, does show a more consistently declining trend.

The magnitudes of S_ρ and other measures reported in Table (1) are not directly comparable. To further ease the comparisons of the patterns of the time trend implied by different measures, we normalize these measures. In particular, we first set the value of all measures in 1976 to 100 and generate normalized values based on the original growth rates. These normalized values are shown in Figure (5). As we can see, while both the measures at the 10th and 25th percentiles traced out the path of S_ρ in the first few years, none of the patterns implied by the conventional measures are consistent with the one by S_ρ. Our measure of the gender gap dropped precipitously before 1990s, but the convergence slowed down since 1990s. Although this result is broadly consistent with the literature (e.g. Blau and Kahn, 2006), the rate of decline implied by our measure is much larger than that by the conventional measures. All traditional measures appear to severely *underestimate* the decline in the gender gap over time. In particular, our S_ρ implies the gender gap narrowed at average annual rate of about 11% during the period 1976-2011, while the annual rate implied by the gender difference at the median is only 5.2% during the same period, the largest among all conventional measures. Intuitively, this makes sense. If the gap at every part of the earnings distributions between men and women decreases, the decrease in the distance between two distributions should be even larger.

4.1.2. Stochastic Dominance Test Results

As discussed above, these measures of the gender gap do not lend themselves to ranking of the earnings distributions between men and women. Therefore, we now to turn to SD tests. SD results are reported in Table (2) and the corresponding comparisons of CDFs over time plotted in Figures (29)-(31). Note that the column labeled *Observed Ranking* details if the distributions can be ranked in either the first or second degree sense; the columns labeled $Pr[d \leq 0]$ and $Pr[s \leq 0]$ report the p-values based on the simple bootstrap technique. If we observe FSD (SSD) *and* $Pr[d \leq 0]$ ($Pr[s \leq 0]$) is large, say 0.90 or higher, we may infer dominance to a desirable degree of confidence.

We first notice that the earnings distribution among men lie predominantly to the right of the earnings distribution among women, indicating higher level of earnings for men. This casual observation is consistent with the fact that the differences in selected percentiles of the earnings distributions between men and women are uniformly positive. According to the SD tests, we, however, fail to find many cases where the earnings distribution among men stochastically dominates the earnings distribution among women. The inability to rank order the earnings distributions between men and women in most cases is informative. This finding implies that any welfare conclusions concerning that women fare worse than men in the labor market are, in most cases, not robust to changes in the particular welfare function being used, despite the fact that the differences in selected percentiles of the earnings distributions between men and women are in many cases positive and in favor of men. This result is in stark contrast with the common belief based on the conventional measures above, illustrating the benefit to considering the *entire* distribution within the welfare economics framework when studying the gender gap.

As we can see from Table (2), we do find stochastic dominance in a few cases. In particular, the earnings distribution among men is found to empirically dominate, in a second-order sense, the earnings distribution among women in 1987; the result is, however, not statistically significant ($p = Pr[d \leq 0] = 0.44$). This result is extremely powerful: any individuals with a social welfare function in the class U_2 (increasing and concave in earnings) would prefer the male distribution to the female distribution, concluding that men perform better than women in the labor market. However, since we do not find FSD, individuals possessing different welfare functions in the class U_1 would disagree about this conclusion. Our SD analysis makes explicit that such a ranking is possible only by accounting for "dispersion" in the welfare criteria. In addition to 1987, we also find second-order dominance in 1988 – 1993, 2002, 2009, and 2011; however, the results are, again, never statistically significant. Among these instances in which we find dominance relations, two findings are noteworthy. First, most cases occurred before 1994. Recall that welfare reforms are enacted by many states in the mid-1990s and by Congress in 1994 (Waldfogel and Mayer, 2000). Our result seems to lend support to effectiveness of the welfare reforms intended to improve women's labor market outcomes. Second, all SSD cases that occurred after 1994 occurred during economic downturns. This result suggests that even though many are impacted by poor economic conditions, women appear to lose more. This finding suggests that even though the welfare reforms seem to improve women's status in general, but do not make them less vulnerable to future recessions.

One interesting question is: Why do we not find any dominance relations in the beginning of the recent recessionary period (2007-2008)? The answer may be that industries such as construction and manufacturing where men are primary workforce are hit harder in the current recession, and as a result, men share a larger burden of the recession than women do (Sahin et al., 2010). Compared the previous recessions, we are therefore less likely to find any dominance relations in the current one. However, there is also evidence that when the economy is further into the recession, men were likely to find jobs faster than women (partly because they work in fields previously dominated by women).[3] The dominance relations are thus more likely to be found.

[3]Source: http://www.pewsocialtrends.org/2011/07/06/two-years-of-economic-recovery-women-lose-jobs-men-find-them/

Examining the CDF figures, we notice that lack of dominance relations is mainly because the earnings distributions of men and women cross at the extreme lower tail. Thus, if not for a few small values, we could have observed dominance relations. Indeed, we do have a small set of individuals earning less than one dollar per hour. The question then comes down to whether these values in the lower tails are due to measurement errors or actually contain useful information of the underlying distributions. To further assess how inclusion of these extremely poor individuals may affect our SD results, as a first step, we exclude those individuals earnings less than one dollar. The results are reported in Table (3). As expected, excluding those with extremely low hourly wages increases the prevalence of the SD relations found. However, increased instances of SD occurred disproportionately in the pre-1994 period. In particular, there are 16 out of 18 years where we find either FSD or SSD. And many of these SD relations are statistically significant. However, when looking at the SD results in the post-1994 period, we find only SD relations in 6 out of 18 years. And half of these cases are not statistically significant. This finding is again consistent with our previous conclusion that after the welfare reforms, we do not find that men necessarily fare better than do women in the labor market. Although we still find SSD in the 2001 recession, we do not find any dominance relations in the current recession, consistent with our interpretation that men were hit harder than women by the current one.

4.2. Counterfactual Analysis

Table (4) reports various measures of the differences between the female wage distribution and the counterfactual wage distribution (#1) (i.e. the distribution of women's wages when their human capital characteristics are paid under men's wage structure). We find that the distance between two distributions is large and statistically significant. Recall that the difference captures only the difference in wage structures between men and women, while holding women's human capital characteristics constant. This result appears to be consistent with the common finding of the importance of wage structure in explaining the wage difference between men and women. The importance of structural difference, however, decreased over time. The implied annualized rate of decline is about 4 percent. In this case, we again find that the implied distance (or importance) varies across various conventional measures, and these measures severely underestimate the rate of the decline.

Turning to the SD results (Table (5)), we find that the female wage distribution and the counterfactual wage distribution # 1 are generally unrankable, in sharp contrast to the conclusion based on the signs of conventional measures. This result implies that, although changing earnings structure would result in a change in the earnings distribution for women, the change is not uniformly in favor of all women. There are some winners and losers. For any individuals with social welfare functions either in U_1 (increasing in wage) or U_2 (increasing in wage and averse to inequality), the change resulted from this type of policy does not necessarily represent a welfare improvement for women. Examining the CDF graphs, we can see that in most cases, the distributions cross at the lower tail. In other words, losers are concentrated in the lower tail of the earnings distribution. When excluding these extremely poor individuals, we do find more cases of dominance relations, implying that changing earnings structure improve women's welfare in these situations (Table (6)). In several years, we find FSD, which implies the change is in favor of *all* women (excluding extremely poor ones). Most of these dominance relations are statistically significant. This implies that wage structure is an important factor in explaining the gender differentials in earnings, and that discrimination may actually exist for the majority of the women in the society. In some cases where we fail to find FSD, we do find SSD; this result means that even though there are losers and winners, the losers are mostly concentrated in the extreme upper tail. As a result, any individuals with social welfare function increasing in wage and averse to inequality would still conclude there exists a welfare improvement for women from changing the wage structure.

Table (7) reports various measures of the differences between the female wage distribution and the counterfactual wage distribution (#2) (i.e. the distribution of women's wages when they possess men's human capital characteristics but holding women's wage structure unchanged). In sharp contrast to the structural difference above, we find that the compositional difference – difference between the female wage distribution and the counterfactual wage distribution (#2) – is, albeit still statistically significant, rather small. In most cases, the magnitude of the compositional difference is only about one tenth of that of the structural effect. However, the magnitude has been increasing over time. The annualized rate of increase is also about 4 percent. Moreover, unlike in the case of structural difference, we find that conventional measures trace out the pattern of our distributional measure well.

Turning to the SD results (Table (8)), we observe no SD ranking of the female wage distribution and the counterfactual wage distribution (#2) in either first or second order sense; this result implies that even if dispersion is incorporated into the welfare criteria, changing the distribution of women's human capital characteristics to the distribution of men's characteristics may not necessarily represent welfare improvement from the societal point of view. Indeed, in some cases where we do find dominance relations, the female wage distribution actually dominates the counterfactual distribution. It implies that women could be even worse off when they have the same distribution of human capital characteristics as do men. The results, however, do not attain statistical significance at conventional levels. Our results are robust to exclusion of those extremely poor individuals (Table (9)).

5. Conclusions

In this paper, we present a set of complementary tools that move beyond the simple moment-based comparison of the earnings distributions. In particular, we propose a new measure of the gender gap based on the the distance between two *whole* earnings distributions, instead of their specific parts. We also introduce tests based on stochastic dominance to allow for robust welfare comparisons of the earnings distributions between men and women. Using the CPS data 1976-2010, we apply this framework to analyze the gender gap in the U.S. We reach two main conclusions. First, we find that traditional moment-based measures severely underestimate the declining trend of the gender gap in the U.S. Second, we find that stochastic dominance is rare; this result implies no clear ranking of the earnings distributions between men and women for welfare criteria generally considered by economists. We find that lack of dominance relations is probably, in many cases, because extremely poor women fare no worse than their male counterparts. When excluding the extremely poor individuals, we do find more cases of dominance relations. Instances in which we do find stochastic dominance appear to be disproportionately concentrated in the periods before the welfare reforms, lending support to the effectiveness of the welfare reforms. Finally, we further compare the female wage distribution to two counterfactual distributions (the earnings that women would earn under the earnings structure of men and the earnings that women would earn should they have men's characteristics). We find that structural effects are generally more important than composition effects. However, the importance of structural effects has declined over time, while that of composition effects has increased. Our SD results of lack of dominance relations in many cases, however, show that neither changing earnings structure nor changing human capital characteristics would necessarily improve women's well-being uniformly in the society.

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Table 1: Measures of The Gender Gaps

Year	$S_\rho \times 100$ (1)	Mean (2)	10th (3)	25th (4)	50th (5)	75th (6)	90th (7)
1976	10.978	0.466	0.362	0.45	0.474	0.472	0.505
1977	10.252	0.444	0.318	0.414	0.488	0.470	0.480
1978	10.155	0.446	0.325	0.416	0.455	0.483	0.474
1979	9.891	0.436	0.288	0.386	0.473	0.495	0.484
1980	9.469	0.422	0.266	0.366	0.472	0.485	0.455
1981	8.957	0.403	0.241	0.354	0.442	0.474	0.459
1982	8.682	0.409	0.270	0.370	0.460	0.475	0.453
1983	7.576	0.387	0.229	0.298	0.433	0.431	0.464
1984	6.505	0.354	0.193	0.297	0.381	0.409	0.405
1985	6.190	0.355	0.209	0.29	0.392	0.414	0.419
1986	5.612	0.339	0.213	0.30	0.373	0.405	0.393
1987	5.009	0.333	0.231	0.297	0.355	0.389	0.382
1988	4.606	0.316	0.199	0.265	0.344	0.375	0.344
1989	4.425	0.315	0.223	0.292	0.359	0.354	0.350
1990	3.602	0.291	0.204	0.241	0.311	0.325	0.317
1991	3.134	0.269	0.163	0.244	0.288	0.306	0.316
1992	2.859	0.259	0.148	0.222	0.285	0.288	0.316
1993	2.662	0.241	0.136	0.21	0.235	0.295	0.289
1994	2.284	0.238	0.146	0.197	0.254	0.276	0.273
1995	2.329	0.248	0.173	0.206	0.260	0.288	0.272
1996	2.259	0.248	0.175	0.218	0.250	0.274	0.272
1997	2.173	0.238	0.160	0.191	0.248	0.262	0.266
1998	2.206	0.243	0.145	0.236	0.258	0.251	0.280
1999	2.320	0.242	0.149	0.230	0.232	0.268	0.274
2000	2.019	0.242	0.158	0.210	0.236	0.273	0.262
2001	2.384	0.266	0.214	0.223	0.266	0.301	0.313
2002	2.271	0.256	0.176	0.239	0.243	0.253	0.310
2003	2.139	0.245	0.182	0.191	0.239	0.262	0.291
2004	1.846	0.234	0.178	0.190	0.218	0.259	0.283
2005	1.908	0.234	0.168	0.182	0.216	0.255	0.288
2006	1.813	0.234	0.173	0.208	0.210	0.254	0.277
2007	1.588	0.224	0.163	0.195	0.244	0.254	0.268
2008	1.582	0.212	0.173	0.167	0.223	0.236	0.258
2009	1.640	0.215	0.154	0.172	0.193	0.222	0.273
2010	1.566	0.211	0.157	0.185	0.203	0.235	0.269
2011	1.436	0.202	0.172	0.185	0.182	0.259	0.248

[1] Data Source: IPUMS CPS (`http://cps.ipums.org/cps/`). Column (1) reports the overal gender gap ($\times$100) at corresponding functionals of the distributions of log wages (measures the distance between the female and male wage distributions). Columns (2)-(6) report conventional measures based on difference in parts of the wage distributions between males and females.

Table 2: Stochastic Dominance Results (Female v.s. Male Wage Distributions)

Year	Observed Ranking	$d_{1,max}$	$d_{2,max}$	d	$Pr[d \leq 0]$	$s_{1,max}$	$s_{2,max}$	s	$Pr[s \leq 0]$
1976	None	54.68	0.03	0.03	0.00	2857.55	4.09	4.09	0.00
1977	None	57.97	0.01	0.01	0.12	2905.85	0.09	0.09	0.25
1978	None	57.07	0.04	0.04	0.01	2926.08	3.87	3.87	0.04
1979	None	57.77	0.03	0.03	0.02	2867.10	2.90	2.90	0.04
1980	None	61.66	0.02	0.02	0.05	2976.71	1.14	1.14	0.10
1981	None	59.44	0.06	0.06	0.03	2787.40	1.69	1.69	0.24
1982	None	54.43	0.01	0.01	0.14	2756.85	0.03	0.03	0.42
1983	None	49.74	0.01	0.01	0.14	2554.90	0.06	0.06	0.24
1984	None	46.47	0.04	0.04	0.00	2188.01	6.93	6.93	0.00
1985	None	46.10	0.02	0.02	0.01	2282.56	0.30	0.30	0.11
1986	None	43.40	0.03	0.03	0.03	2062.14	0.82	0.82	0.07
1987	SSD	41.47	0.02	0.02	0.02	2046.66	0.00	0.00	0.44
1988	SSD	40.25	0.01	0.01	0.07	2054.63	0.00	0.00	0.68
1989	SSD	37.94	0.03	0.03	0.11	1985.95	0.00	0.00	0.58
1990	SSD	35.94	0.01	0.01	0.03	3050.52	-0.01	-0.01	0.72
1991	None	33.32	0.01	0.01	0.02	2581.72	0.81	0.81	0.12
1992	SSD	31.99	0.02	0.02	0.14	1639.89	0.00	0.00	0.67
1993	SSD	30.24	0.07	0.07	0.02	1589.28	0.00	0.00	0.68
1994	None	27.94	0.02	0.02	0.03	1745.41	1.36	1.36	0.14
1995	None	28.74	0.03	0.03	0.00	1852.25	2.23	2.23	0.06
1996	None	25.73	0.02	0.02	0.01	1592.90	0.63	0.63	0.06
1997	None	26.14	0.05	0.05	0.00	1289.10	5.35	5.35	0.01
1998	None	26.18	0.11	0.11	0.00	1397.55	7.12	7.12	0.00
1999	None	26.50	0.13	0.13	0.00	1544.22	2.43	2.43	0.05
2000	None	25.93	0.04	0.04	0.03	1610.06	0.07	0.07	0.23
2001	None	34.60	0.05	0.05	0.00	2020.53	0.09	0.09	0.25
2002	SSD	33.76	0.29	0.29	0.00	1912.43	0.00	0.00	0.53
2003	None	31.19	0.14	0.14	0.00	1699.84	1.08	1.08	0.29
2004	None	30.20	0.05	0.05	0.00	1871.37	1.33	1.33	0.02
2005	None	30.10	0.08	0.08	0.00	1706.26	9.96	9.96	0.00
2006	None	29.25	0.02	0.02	0.01	1576.49	0.67	0.67	0.21
2007	None	27.94	0.03	0.03	0.00	1636.49	2.27	2.27	0.02
2008	None	27.49	0.08	0.08	0.00	1874.15	0.55	0.55	0.10
2009	SSD	27.64	0.04	0.04	0.01	1532.20	0.00	0.00	0.49
2010	None	27.29	0.30	0.30	0.00	1467.64	6.00	6.00	0.00
2011	SSD	25.04	0.01	0.01	0.14	1416.84	0.00	0.00	0.61

Table 3: Stochastic Dominance Results (Female v.s. Male Wage Distributions)

Year	Observed Ranking	$d_{1,max}$	$d_{2,max}$	d	$Pr[d \leq 0]$	$s_{1,max}$	$s_{2,max}$	s	$Pr[s \leq 0]$
1976	FSD	54.39	0.00	0.00	0.78	8763.44	0.00	0.00	0.98
1977	SSD	57.82	0.00	0.00	0.43	9157.44	0.00	0.00	1.00
1978	FSD	57.01	0.00	0.00	0.60	8789.47	0.00	0.00	0.94
1979	FSD	57.75	0.00	0.00	0.95	8223.35	0.00	0.00	0.99
1980	FSD	61.62	0.00	0.00	0.57	8637.30	0.00	0.00	1.00
1981	SSD	59.50	0.00	0.00	0.90	8609.25	0.00	0.00	0.96
1982	SSD	54.37	0.01	0.01	0.19	7988.57	0.00	0.00	1.00
1983	SSD	49.92	0.01	0.01	0.24	7622.75	0.00	0.00	0.75
1984	None	46.58	0.02	0.02	0.22	6557.96	0.14	0.14	0.30
1985	SSD	46.15	0.01	0.01	0.12	6138.84	0.00	0.00	0.95
1986	SSD	43.56	0.00	0.00	0.51	5822.90	0.00	0.00	0.76
1987	FSD	41.46	0.00	0.00	0.33	5873.88	0.00	0.00	0.74
1988	SSD	40.27	0.01	0.01	0.29	5286.97	0.00	0.00	0.93
1989	None	37.92	0.02	0.02	0.19	5119.93	0.05	0.05	0.25
1990	SSD	35.95	0.01	0.01	0.10	4881.27	0.00	0.00	0.99
1991	SSD	33.32	0.01	0.01	0.33	4778.64	0.00	0.00	0.99
1992	SSD	32.10	0.00	0.00	0.62	4356.55	0.00	0.00	0.67
1993	FSD	30.33	0.00	0.00	0.59	4223.63	0.00	0.00	0.82
1994	None	27.94	0.01	0.01	0.12	3690.67	0.02	0.02	0.55
1995	SSD	28.68	0.02	0.02	0.05	4042.33	0.00	0.00	0.90
1996	None	25.61	0.04	0.04	0.01	2755.98	0.04	0.04	0.26
1997	SSD	26.14	0.05	0.05	0.00	3061.76	0.00	0.00	0.72
1998	None	26.14	0.04	0.04	0.03	3141.59	0.11	0.11	0.35
1999	None	26.38	0.13	0.13	0.00	3181.43	0.18	0.18	0.25
2000	None	25.80	0.04	0.04	0.02	3311.25	0.01	0.01	0.37
2001	None	34.56	0.05	0.05	0.00	4410.62	0.00	0.00	0.71
2002	SSD	33.70	0.31	0.31	0.00	4208.18	0.00	0.00	0.76
2003	SSD	31.20	0.14	0.14	0.00	3876.47	0.00	0.00	0.99
2004	SSD	30.13	0.05	0.05	0.00	3707.81	0.00	0.00	0.97
2005	None	30.20	0.08	0.08	0.00	3411.13	0.09	0.09	0.21
2006	SSD	29.23	0.01	0.01	0.24	3578.18	0.00	0.00	0.97
2007	None	27.79	0.02	0.02	0.09	3470.53	0.04	0.04	0.17
2008	None	27.60	0.08	0.08	0.00	3268.23	0.38	0.38	0.16
2009	None	27.65	0.05	0.05	0.00	3205.33	0.98	0.98	0.04
2010	None	27.41	0.30	0.30	0.00	3068.48	0.05	0.05	0.32
2011	None	25.08	0.01	0.01	0.19	2991.99	0.04	0.04	0.40

Table 4: MEASURES OF DIFFERENCES BETWEEN FEMALE AND FEMALE COUNTERFACTUAL #1 DISTRIBUTIONS

Year	$S_\rho \times 100$ (1)	Mean (2)	10th (3)	25th (4)	50th (5)	75th (6)	90th (7)
1976	8.998	0.417	0.317	0.383	0.431	0.438	0.460
1977	8.517	0.399	0.268	0.376	0.427	0.427	0.431
1978	8.565	0.403	0.276	0.349	0.412	0.448	0.452
1979	8.438	0.400	0.248	0.347	0.433	0.454	0.470
1980	8.400	0.402	0.262	0.340	0.432	0.468	0.436
1981	8.117	0.383	0.223	0.332	0.417	0.452	0.436
1982	7.885	0.389	0.270	0.341	0.428	0.438	0.428
1983	6.709	0.363	0.221	0.293	0.405	0.400	0.423
1984	6.151	0.346	0.199	0.293	0.375	0.397	0.392
1985	6.052	0.355	0.214	0.290	0.392	0.394	0.419
1986	5.457	0.334	0.218	0.300	0.373	0.405	0.393
1987	4.853	0.333	0.261	0.297	0.346	0.368	0.378
1988	4.636	0.323	0.228	0.274	0.344	0.375	0.340
1989	4.791	0.334	0.239	0.305	0.363	0.358	0.368
1990	4.181	0.319	0.257	0.288	0.336	0.340	0.339
1991	3.782	0.302	0.208	0.277	0.327	0.320	0.334
1992	3.622	0.299	0.198	0.282	0.310	0.315	0.316
1993	3.401	0.283	0.195	0.257	0.289	0.331	0.325
1994	3.036	0.280	0.223	0.257	0.300	0.312	0.307
1995	2.922	0.281	0.191	0.251	0.303	0.288	0.305
1996	3.050	0.294	0.210	0.272	0.297	0.304	0.316
1997	3.059	0.294	0.240	0.271	0.297	0.297	0.310
1998	3.101	0.296	0.210	0.288	0.292	0.307	0.344
1999	3.388	0.298	0.244	0.279	0.297	0.308	0.313
2000	3.165	0.308	0.248	0.287	0.307	0.332	0.318
2001	3.176	0.310	0.243	0.275	0.320	0.309	0.366
2002	3.215	0.309	0.240	0.288	0.288	0.313	0.364
2003	2.862	0.287	0.234	0.234	0.267	0.312	0.342
2004	2.641	0.283	0.227	0.250	0.273	0.312	0.312
2005	2.900	0.295	0.232	0.223	0.288	0.319	0.348
2006	2.811	0.296	0.223	0.262	0.288	0.323	0.359
2007	2.531	0.283	0.220	0.260	0.283	0.305	0.331
2008	2.640	0.279	0.242	0.243	0.279	0.300	0.324
2009	2.680	0.281	0.248	0.245	0.278	0.296	0.357
2010	2.589	0.278	0.223	0.262	0.280	0.307	0.325
2011	2.119	0.249	0.223	0.237	0.239	0.304	0.297

[1] Data Source: IPUMS CPS (`http://cps.ipums.org/cps/`). Column (1) reports the overal gender gap ($\times 100$) at corresponding functionals of the distributions of log wages (measures the distance between the female and female counterfactual #1 wage distributions). Columns (2)- (6) report conventional measures based on difference in parts of between the female and female counterfactual #1 wage distributions. Female counterfactual #1 distribution is the counterfactual wage distribution among women when their human characteristics are valued under men's wage structure.

Table 5: Stochastic Dominance Results (Female v.s. Female Counterfactual #1 Wage Distributions)

Year	Observed Ranking	$d_{1,max}$	$d_{2,max}$	d	$Pr[d \leq 0]$	$s_{1,max}$	$s_{2,max}$	s	$Pr[s \leq 0]$
1976	None	48.80	0.05	0.05	0.00	2555.98	8.61	8.61	0.00
1977	None	52.75	0.01	0.01	0.07	2613.64	0.04	0.04	0.29
1978	None	52.08	0.07	0.07	0.00	2642.36	6.66	6.66	0.03
1979	None	53.30	0.01	0.01	0.01	2633.72	0.53	0.53	0.03
1980	None	58.25	0.00	0.00	0.09	2834.30	0.02	0.02	0.18
1981	None	56.46	0.01	0.01	0.15	2649.36	0.61	0.61	0.39
1982	None	51.51	0.01	0.01	0.08	2621.23	0.07	0.07	0.41
1983	None	46.69	0.00	0.00	0.22	2397.27	0.05	0.05	0.32
1984	None	45.11	0.05	0.05	0.00	2139.66	9.55	9.55	0.00
1985	None	45.91	0.02	0.02	0.02	2280.43	0.17	0.17	0.29
1986	None	42.81	0.11	0.11	0.00	2031.67	15.76	15.76	0.01
1987	SSD	40.69	0.01	0.01	0.12	2049.58	0.00	0.00	0.58
1988	SSD	40.49	0.01	0.01	0.11	2098.89	0.00	0.00	0.77
1989	FSD	39.33	0.00	0.00	0.34	2104.89	0.00	0.00	0.71
1990	SSD	39.34	0.01	0.01	0.03	3343.10	-0.01	-0.01	0.80
1991	None	37.25	0.01	0.01	0.03	2895.32	0.90	0.90	0.13
1992	SSD	36.24	0.01	0.01	0.17	1894.01	0.00	0.00	0.51
1993	SSD	34.45	0.03	0.03	0.17	1866.90	0.00	0.00	0.89
1994	None	32.44	0.04	0.04	0.02	2052.54	3.17	3.17	0.12
1995	None	32.31	0.02	0.02	0.01	2097.93	0.16	0.16	0.16
1996	None	30.16	0.03	0.03	0.01	1884.95	0.29	0.29	0.08
1997	None	31.34	0.06	0.06	0.00	1595.30	0.22	0.22	0.08
1998	None	30.86	0.06	0.06	0.00	1702.46	2.94	2.94	0.01
1999	None	32.35	0.15	0.15	0.00	1902.90	3.58	3.58	0.05
2000	None	33.06	0.06	0.06	0.00	2048.22	0.06	0.06	0.25
2001	None	40.36	0.05	0.05	0.00	2356.72	0.03	0.03	0.28
2002	None	40.70	0.28	0.28	0.00	2304.72	0.26	0.26	0.38
2003	None	36.60	0.10	0.10	0.00	1997.48	0.37	0.37	0.36
2004	None	36.12	0.05	0.05	0.00	2268.42	1.41	1.41	0.02
2005	None	37.79	0.07	0.07	0.00	2151.03	9.92	9.92	0.00
2006	None	37.17	0.02	0.02	0.04	1996.49	0.31	0.31	0.37
2007	None	35.82	0.07	0.07	0.00	2068.00	5.82	5.82	0.01
2008	None	36.34	0.08	0.08	0.00	2473.21	0.13	0.13	0.07
2009	SSD	35.54	0.02	0.02	0.02	2001.85	0.00	0.00	0.62
2010	None	35.37	0.29	0.29	0.00	1936.56	5.84	5.84	0.00
2011	SSD	30.61	0.01	0.01	0.16	1746.44	0.00	0.00	0.92

Table 6: Stochastic Dominance Results (Female v.s. Female Counterfactual #1 Wage Distributions)

Year	Observed Ranking	$d_{1,max}$	$d_{2,max}$	d	$Pr[d \leq 0]$	$s_{1,max}$	$s_{2,max}$	s	$Pr[s \leq 0]$
1976	FSD	48.91	0.00	0.00	0.78	7905.70	0.00	0.00	0.97
1977	SSD	52.53	0.01	0.01	0.30	8223.91	0.00	0.00	1.00
1978	None	52.08	0.04	0.04	0.18	7985.76	0.11	0.11	0.41
1979	FSD	53.34	0.00	0.00	0.70	7536.77	0.00	0.00	0.85
1980	FSD	58.01	0.00	0.00	0.40	8149.29	0.00	0.00	1.00
1981	FSD	56.39	0.00	0.00	0.75	8140.53	0.00	0.00	0.90
1982	SSD	51.58	0.01	0.01	0.25	7616.01	0.00	0.00	1.00
1983	None	46.78	0.04	0.04	0.16	7142.87	0.09	0.09	0.45
1984	None	45.18	0.01	0.01	0.24	6366.37	0.05	0.05	0.38
1985	SSD	45.96	0.02	0.02	0.17	6096.31	0.00	0.00	0.99
1986	FSD	42.95	0.00	0.00	0.56	5780.21	0.00	0.00	0.92
1987	FSD	40.68	0.00	0.00	0.32	5873.56	0.00	0.00	0.74
1988	SSD	40.48	0.01	0.01	0.30	5383.77	0.00	0.00	1.00
1989	None	39.31	0.02	0.02	0.35	5402.91	0.13	0.13	0.42
1990	SSD	39.35	0.01	0.01	0.13	5347.55	0.00	0.00	0.99
1991	SSD	37.43	0.01	0.01	0.32	5341.22	0.00	0.00	0.94
1992	FSD	36.54	0.00	0.00	0.65	5013.92	0.00	0.00	0.72
1993	FSD	34.57	0.00	0.00	0.84	4924.65	0.00	0.00	0.99
1994	SSD	32.55	0.00	0.00	0.26	4366.28	0.00	0.00	0.86
1995	SSD	32.31	0.02	0.02	0.04	4571.86	0.00	0.00	0.87
1996	None	30.12	0.03	0.03	0.01	3255.89	0.04	0.04	0.28
1997	SSD	31.34	0.06	0.06	0.00	3724.34	0.00	0.00	0.97
1998	SSD	30.84	0.04	0.04	0.09	3795.02	0.00	0.00	0.49
1999	SSD	32.29	0.15	0.15	0.00	3924.22	0.00	0.00	0.54
2000	None	32.96	0.07	0.07	0.00	4240.92	0.00	0.00	0.27
2001	None	40.41	0.05	0.05	0.00	5152.16	0.00	0.00	0.96
2002	SSD	40.67	0.30	0.30	0.00	5089.80	0.00	0.00	0.75
2003	SSD	36.63	0.10	0.10	0.00	4538.40	0.00	0.00	1.00
2004	SSD	36.01	0.05	0.05	0.00	4485.02	0.00	0.00	0.99
2005	None	37.78	0.05	0.05	0.01	4292.80	0.03	0.03	0.27
2006	SSD	37.20	0.01	0.01	0.24	4511.61	0.00	0.00	0.87
2007	None	35.81	0.03	0.03	0.02	4422.77	0.13	0.13	0.07
2008	None	36.37	0.08	0.08	0.00	4328.54	0.19	0.19	0.29
2009	None	35.53	0.03	0.03	0.00	4174.76	0.54	0.54	0.09
2010	None	35.42	0.29	0.29	0.00	4055.27	0.05	0.05	0.33
2011	FSD	30.68	0.00	0.00	0.36	3688.23	0.00	0.00	0.78

Table 7: MEASURES OF DIFFERENCES BETWEEN FEMALE AND FEMALE COUNTERFACTUAL #2 DISTRIBUTIONS

Year	$S_\rho \times 100$ (1)	Mean (2)	10th (3)	25th (4)	50th (5)	75th (6)	90th (7)
1976	0.117	-0.026	-0.038	-0.032	-0.050	-0.023	0.000
1977	0.124	-0.030	-0.012	-0.041	-0.047	-0.010	0.000
1978	0.121	-0.032	-0.059	-0.048	-0.049	-0.017	0.000
1979	0.068	-0.022	-0.038	-0.036	-0.035	-0.018	0.000
1980	0.118	-0.041	-0.039	-0.049	-0.026	-0.025	-0.008
1981	0.155	-0.037	-0.079	-0.067	-0.028	-0.010	-0.003
1982	0.159	-0.041	-0.066	-0.051	-0.047	-0.029	-0.001
1983	0.158	-0.043	-0.065	-0.084	-0.036	-0.024	0.000
1984	0.157	-0.041	-0.057	-0.065	-0.069	-0.028	-0.025
1985	0.206	-0.057	-0.065	-0.078	-0.057	-0.043	0.000
1986	0.179	-0.052	-0.051	-0.051	-0.059	-0.004	-0.021
1987	0.204	-0.054	-0.053	-0.065	-0.069	-0.037	-0.004
1988	0.221	-0.061	-0.107	-0.095	-0.057	-0.031	-0.013
1989	0.246	-0.064	-0.102	-0.111	-0.065	-0.044	-0.028
1990	0.240	-0.069	-0.086	-0.107	-0.069	-0.046	-0.026
1991	0.334	-0.082	-0.100	-0.104	-0.116	-0.066	-0.036
1992	0.323	-0.078	-0.086	-0.109	-0.099	-0.075	-0.029
1993	0.297	-0.077	-0.077	-0.111	-0.104	-0.055	-0.031
1994	0.305	-0.084	-0.082	-0.111	-0.094	-0.068	-0.020
1995	0.242	-0.070	-0.098	-0.108	-0.079	-0.053	-0.029
1996	0.268	-0.075	-0.086	-0.088	-0.091	-0.047	-0.038
1997	0.284	-0.074	-0.073	-0.129	-0.078	-0.039	-0.046
1998	0.309	-0.084	-0.078	-0.079	-0.113	-0.086	-0.039
1999	0.369	-0.090	-0.094	-0.123	-0.125	-0.072	-0.059
2000	0.326	-0.086	-0.095	-0.078	-0.095	-0.059	-0.041
2001	0.232	-0.069	-0.061	-0.093	-0.056	-0.056	-0.039
2002	0.264	-0.078	-0.073	-0.090	-0.085	-0.072	-0.045
2003	0.204	-0.067	-0.080	-0.103	-0.097	-0.051	-0.037
2004	0.280	-0.081	-0.100	-0.097	-0.091	-0.050	-0.069
2005	0.357	-0.092	-0.119	-0.123	-0.109	-0.049	-0.049
2006	0.342	-0.091	-0.074	-0.105	-0.128	-0.082	-0.059
2007	0.340	-0.093	-0.105	-0.085	-0.084	-0.079	-0.069
2008	0.334	-0.087	-0.079	-0.095	-0.079	-0.074	-0.061
2009	0.336	-0.093	-0.077	-0.130	-0.105	-0.105	-0.074
2010	0.305	-0.088	-0.065	-0.104	-0.125	-0.086	-0.041
2011	0.487	-0.112	-0.065	-0.152	-0.154	-0.093	-0.088

[1] Data Source: IPUMS CPS (`http://cps.ipums.org/cps/`). Column (1) reports the overal gender gap ($\times$100) at corresponding functionals of the distributions of log wages (measures the distance between the female and female counterfactual #2 wage distributions). Columns (2)- (6) report conventional measures based on difference in parts of between the female and female counterfactual #2 wage distributions. Female counterfactual #2 distribution is the counterfactual wage distribution among women when men's human characteristics are instead valued under women's wage structure.

Table 8: STOCHASTIC DOMINANCE RESULTS (FEMALE V.S. FEMALE COUNTERFACTUAL #2 WAGE DISTRIBUTIONS)

Year	Observed Ranking	$d_{1,max}$	$d_{2,max}$	d	$Pr[d \leq 0]$	$s_{1,max}$	$s_{2,max}$	s	$Pr[s \leq 0]$
1976	None	0.29	5.59	0.29	0.00	9.32	167.48	9.32	0.06
1977	None	0.47	6.50	0.47	0.00	4.62	205.10	4.62	0.05
1978	None	0.51	6.58	0.51	0.00	1.12	216.97	1.12	0.26
1979	SSD	0.43	4.60	0.43	0.00	0.00	149.68	0.00	0.38
1980	SSD	0.16	6.47	0.16	0.07	0.00	291.31	0.00	0.71
1981	None	0.14	8.14	0.14	0.00	4.75	254.96	4.75	0.11
1982	None	0.18	7.69	0.18	0.00	3.29	276.39	3.29	0.10
1983	SSD	0.02	7.23	0.02	0.01	0.00	285.88	0.00	0.57
1984	None	0.08	7.42	0.08	0.00	13.72	252.67	13.72	0.01
1985	None	0.01	8.55	0.01	0.01	0.02	363.81	0.02	0.29
1986	None	0.04	8.26	0.04	0.00	3.00	315.77	3.00	0.06
1987	None	0.06	8.67	0.06	0.00	9.87	332.08	9.87	0.02
1988	None	0.02	9.23	0.02	0.01	1.47	391.56	1.47	0.14
1989	None	0.04	9.59	0.04	0.00	3.94	400.38	3.94	0.01
1990	None	0.03	9.68	0.03	0.01	1.37	720.30	1.37	0.11
1991	SSD	0.00	12.27	0.00	0.04	0.00	782.51	0.00	0.39
1992	None	0.03	11.75	0.03	0.00	2.71	494.96	2.71	0.03
1993	None	0.04	11.12	0.04	0.00	3.40	510.03	3.40	0.04
1994	FSD	0.00	10.91	0.00	0.09	0.00	611.93	0.00	0.67
1995	None	0.01	9.86	0.01	0.05	0.68	525.36	0.68	0.22
1996	SSD	0.00	10.21	0.00	0.04	0.00	480.45	0.00	0.31
1997	None	0.10	10.02	0.10	0.00	5.67	401.50	5.67	0.00
1998	None	0.06	11.11	0.06	0.03	0.07	481.52	0.07	0.37
1999	None	0.05	12.03	0.05	0.00	1.76	573.10	1.76	0.03
2000	None	0.02	11.54	0.02	0.00	1.83	572.13	1.83	0.07
2001	None	0.01	12.41	0.01	0.01	0.63	527.40	0.63	0.25
2002	None	0.02	12.55	0.02	0.02	0.26	585.00	0.26	0.31
2003	SSD	0.04	11.00	0.04	0.00	0.00	463.46	0.00	0.36
2004	FSD	0.00	13.07	0.00	0.07	0.00	649.16	0.00	0.52
2005	None	0.03	14.22	0.03	0.00	1.53	673.25	1.53	0.16
2006	None	0.03	14.24	0.03	0.01	2.45	614.94	2.45	0.03
2007	None	0.03	14.09	0.03	0.00	2.42	674.54	2.42	0.11
2008	None	0.08	13.70	0.08	0.00	3.72	771.60	3.72	0.13
2009	SSD	0.02	14.04	0.02	0.11	0.00	659.49	0.00	0.74
2010	None	0.02	13.22	0.02	0.01	0.04	608.87	0.04	0.35
2011	FSD	0.00	15.98	0.00	0.02	0.00	783.84	0.00	0.32

Table 9: STOCHASTIC DOMINANCE RESULTS (FEMALE V.S. FEMALE COUNTERFACTUAL #2 WAGE DISTRIBUTIONS)

Year	Observed Ranking	$d_{1,max}$	$d_{2,max}$	d	$Pr[d \leq 0]$	$s_{1,max}$	$s_{2,max}$	s	$Pr[s \leq 0]$
1976	SSD	0.27	6.05	0.27	0.00	0.00	612.86	0.00	0.63
1977	None	0.44	6.76	0.44	0.00	0.06	649.61	0.06	0.50
1978	SSD	0.47	6.94	0.47	0.00	0.00	636.94	0.00	0.81
1979	SSD	0.39	5.06	0.39	0.01	0.00	453.80	0.00	0.56
1980	SSD	0.16	6.30	0.16	0.07	0.00	651.55	0.00	0.74
1981	None	0.14	8.16	0.14	0.03	0.00	760.45	0.00	0.62
1982	SSD	0.17	7.56	0.17	0.01	0.00	730.73	0.00	0.71
1983	SSD	0.03	7.28	0.03	0.02	0.00	720.18	0.00	0.36
1984	None	0.06	7.44	0.06	0.02	0.62	816.19	0.62	0.24
1985	None	0.04	8.44	0.04	0.01	0.10	883.48	0.10	0.30
1986	SSD	0.05	8.30	0.05	0.01	0.00	874.34	0.00	0.36
1987	SSD	0.01	8.74	0.01	0.05	0.00	975.29	0.00	0.56
1988	None	0.01	9.24	0.01	0.09	0.01	983.77	0.01	0.34
1989	None	0.01	9.59	0.01	0.02	0.01	1017.43	0.01	0.48
1990	FSD	0.00	9.65	0.00	0.27	0.00	1139.59	0.00	0.86
1991	SSD	0.00	12.30	0.00	0.09	0.00	1439.04	0.00	0.63
1992	SSD	0.03	11.78	0.03	0.02	0.00	1330.50	0.00	0.41
1993	SSD	0.03	11.07	0.03	0.02	0.00	1331.55	0.00	0.59
1994	None	0.01	10.81	0.01	0.02	0.08	1200.98	0.08	0.15
1995	SSD	0.00	9.95	0.00	0.08	0.00	1159.20	0.00	0.42
1996	SSD	0.03	10.30	0.03	0.05	0.00	818.91	0.00	0.39
1997	None	0.03	10.03	0.03	0.01	0.02	959.20	0.02	0.32
1998	FSD	0.00	11.18	0.00	0.09	0.00	1081.99	0.00	0.51
1999	None	0.01	12.07	0.01	0.05	0.04	1175.68	0.04	0.34
2000	None	0.02	11.71	0.02	0.05	0.17	1219.36	0.17	0.20
2001	None	0.02	12.44	0.02	0.02	0.07	1170.30	0.07	0.25
2002	None	0.01	12.62	0.01	0.02	0.05	1282.92	0.05	0.24
2003	None	0.04	11.02	0.04	0.01	0.08	1059.72	0.08	0.19
2004	None	0.01	13.05	0.01	0.10	0.02	1295.15	0.02	0.56
2005	None	0.02	14.31	0.02	0.01	0.11	1351.52	0.11	0.05
2006	SSD	0.01	14.33	0.01	0.10	0.00	1415.75	0.00	0.55
2007	None	0.05	14.23	0.05	0.01	0.04	1444.61	0.04	0.25
2008	None	0.02	13.76	0.02	0.01	0.10	1381.99	0.10	0.15
2009	None	0.02	14.01	0.02	0.01	0.32	1325.55	0.32	0.07
2010	None	0.03	13.28	0.03	0.01	0.13	1264.91	0.13	0.27
2011	None	0.03	16.01	0.03	0.01	0.34	1658.08	0.34	0.09

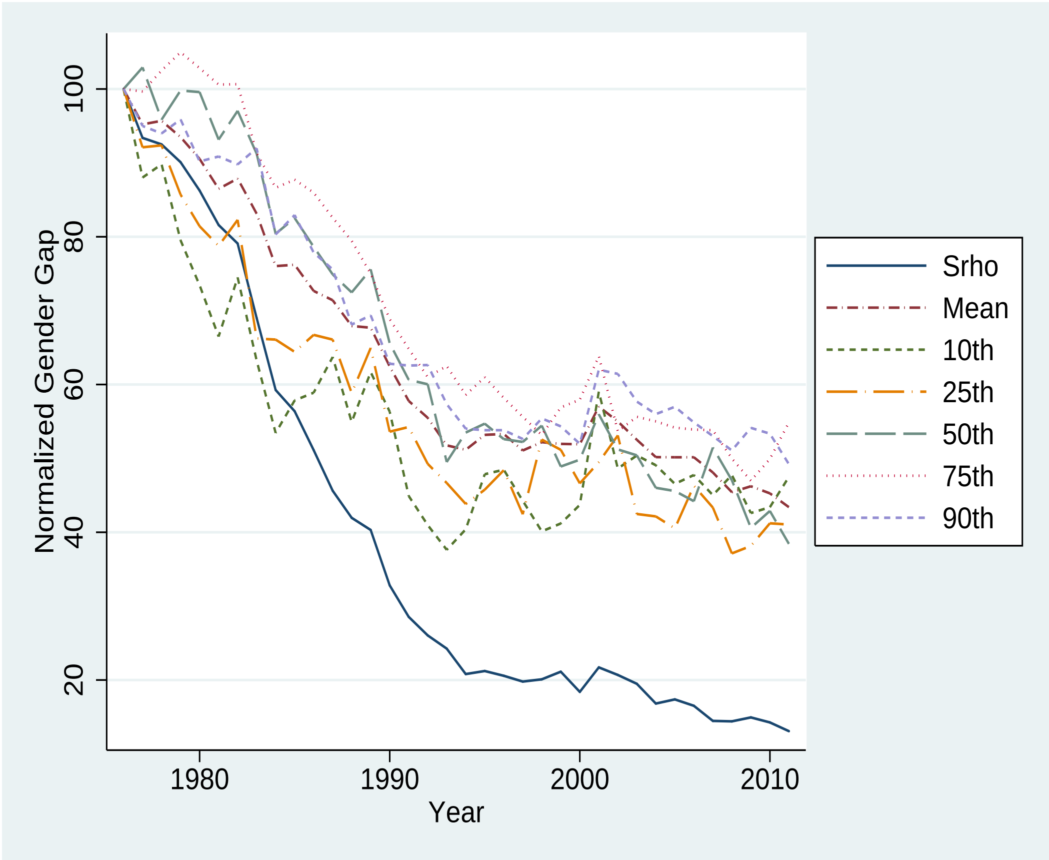
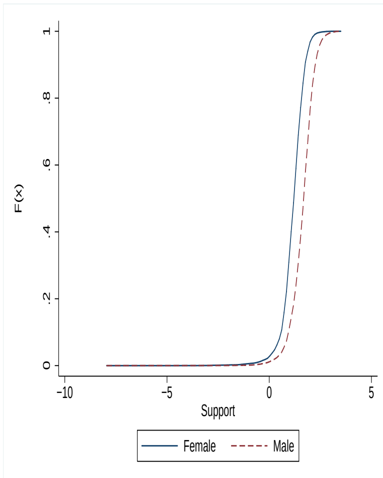
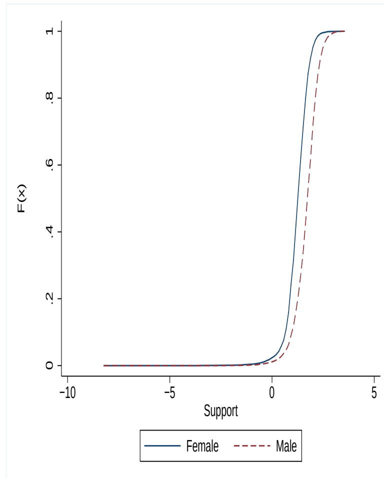


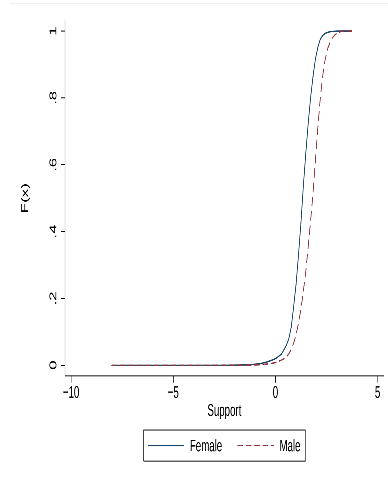
Figure 1: The Trend of Gender Wage Gap



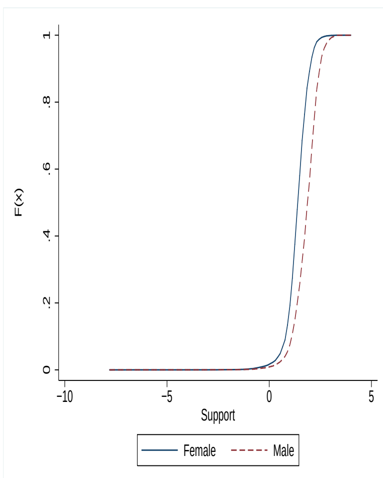
(a) 1976



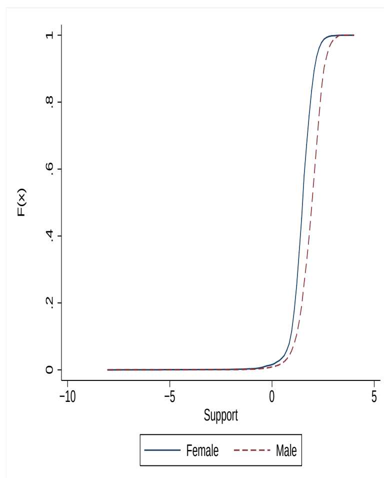
(b) 1977



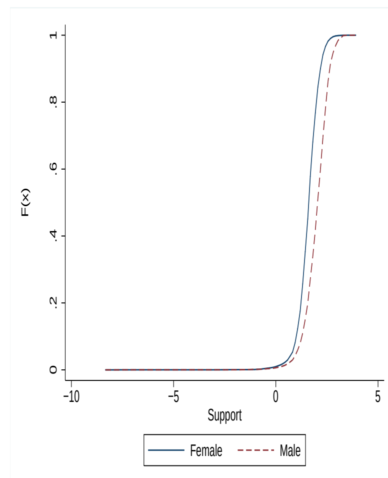
(c) 1978



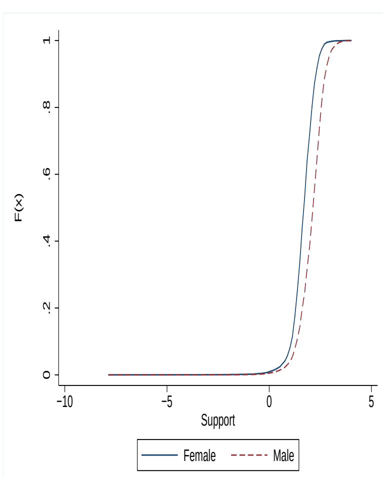
(d) 1979



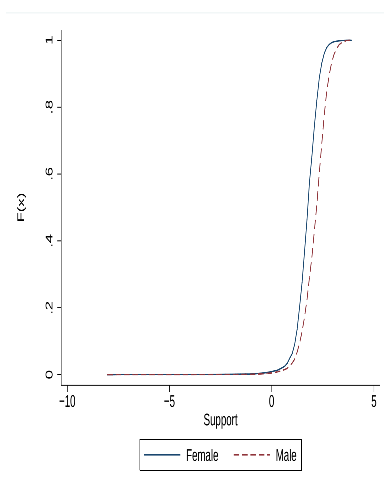
(e) 1980



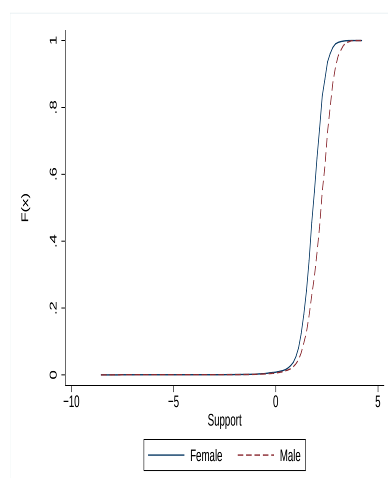
(f) 1981



(g) 1982

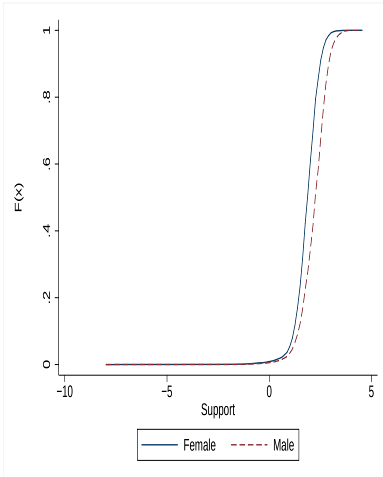


(h) 1983

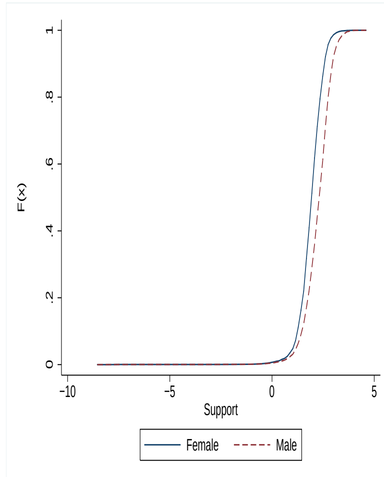


(i) 1984

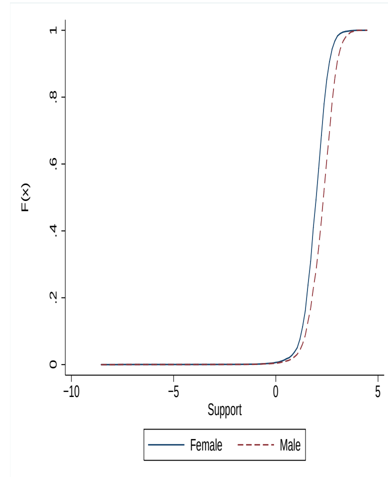
Figure 2: CDF Comparisons of Female and Male Wage Distributions (1976-1984)



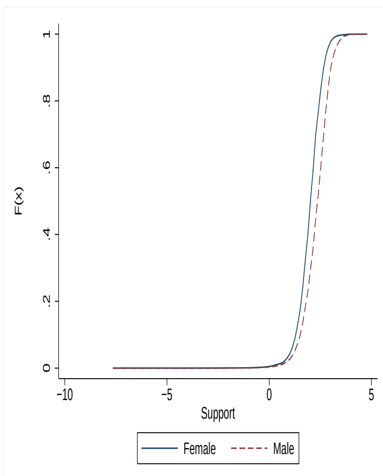
(a) 1985



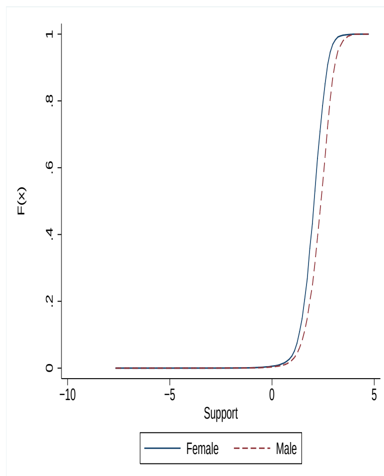
(b) 1986



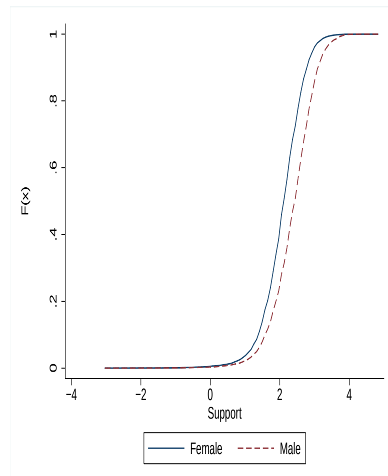
(c) 1987



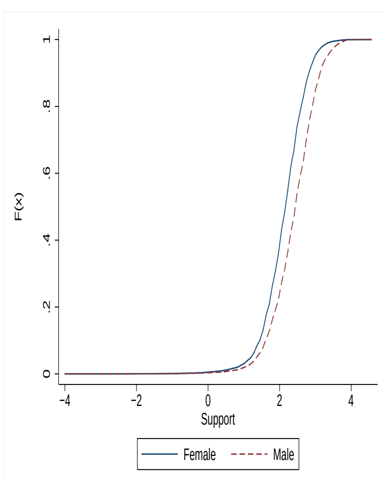
(d) 1988



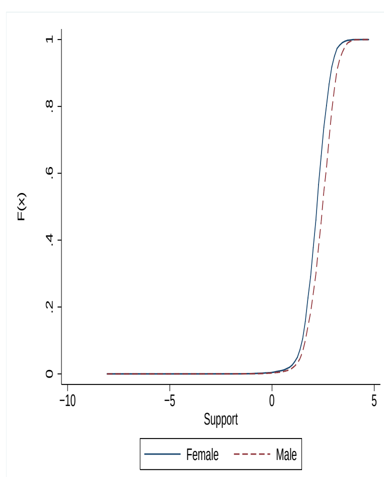
(e) 1989



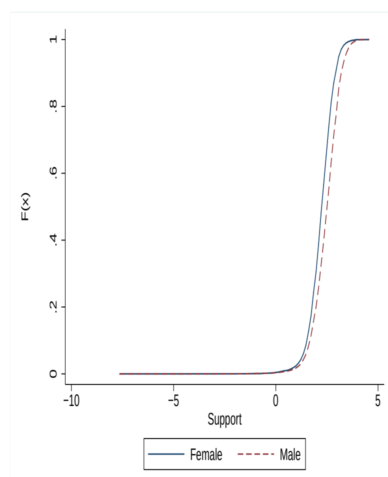
(f) 1990



(g) 1991

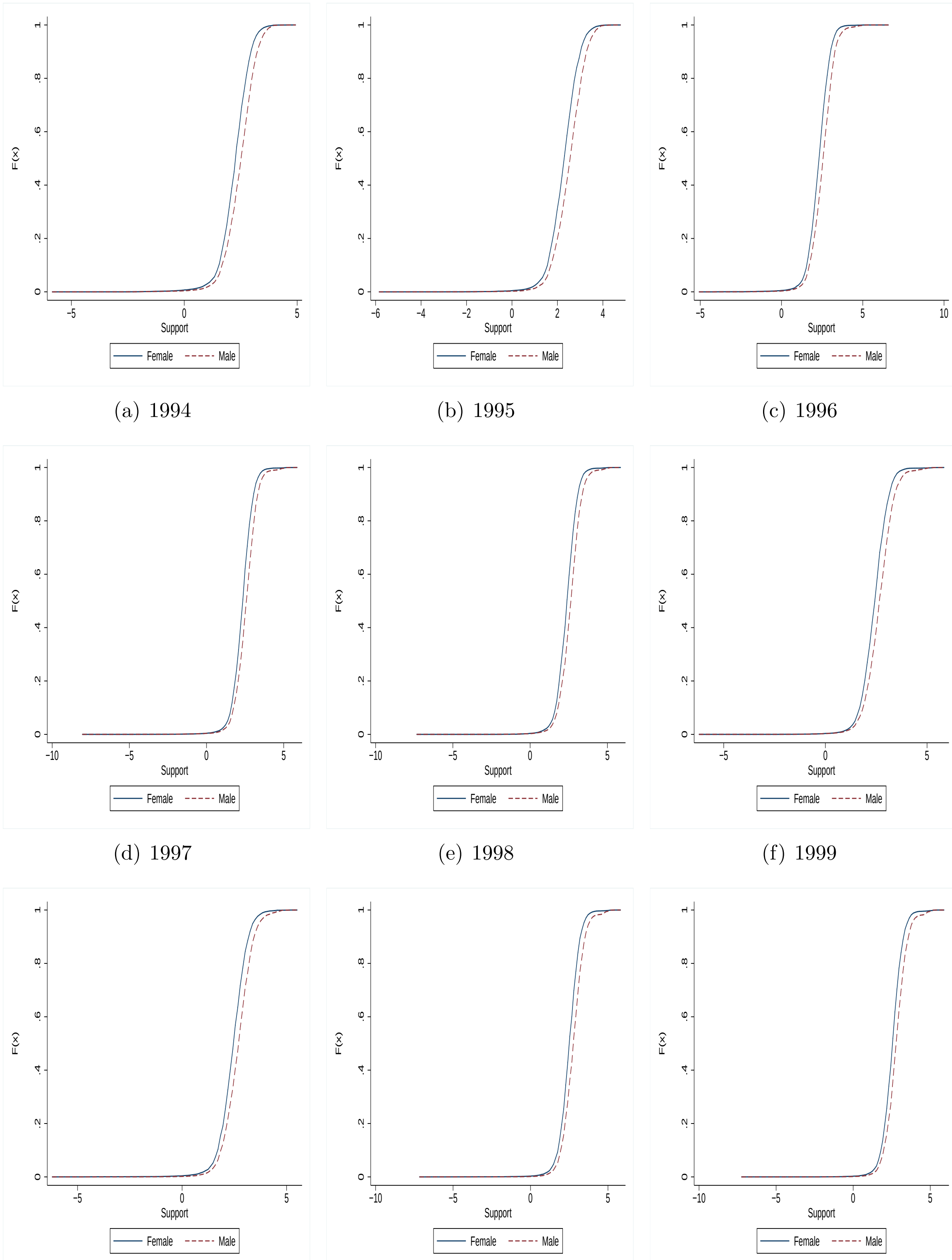


(h) 1992



(i) 1993

Figure 3: CDF Comparisons of Female and Male Wage Distributions (1985 - 1993)

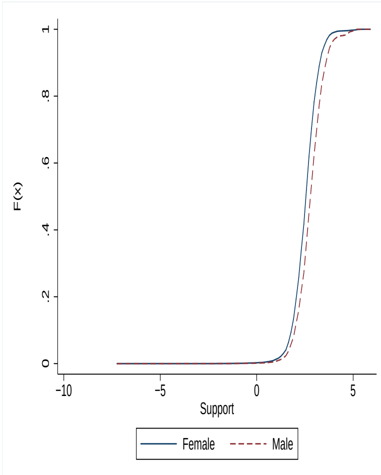


(a) 1994 (b) 1995 (c) 1996

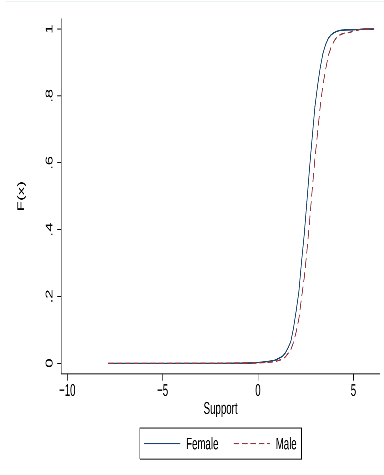
(d) 1997 (e) 1998 (f) 1999

(g) 2000 (h) 2001 (i) 2002

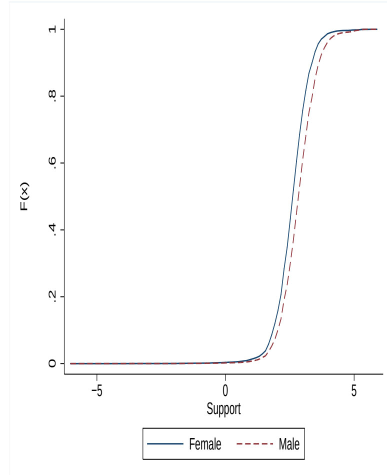
Figure 4: CDF Comparisons of Female and Male Wage Distributions (1994 - 2002)



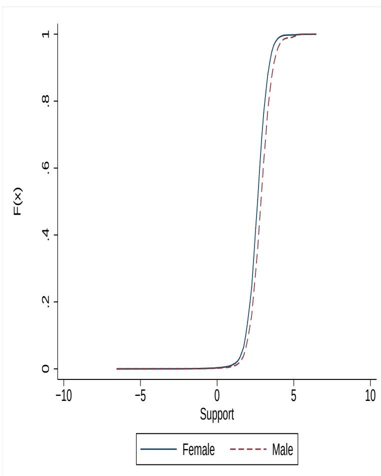
(a) 2002



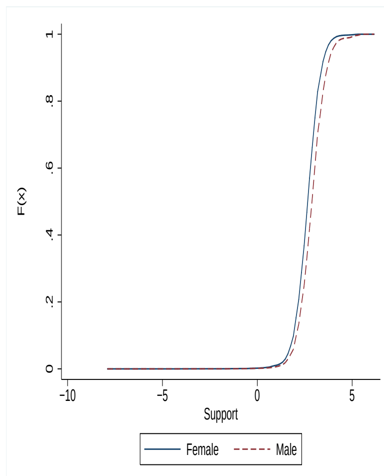
(b) 2003



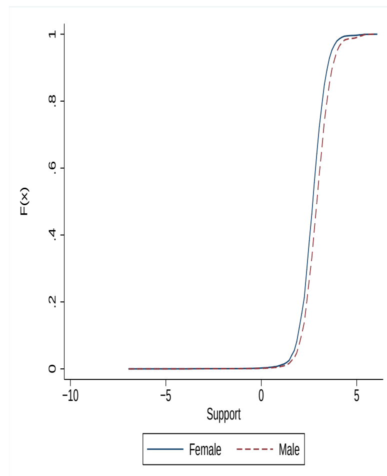
(c) 2004



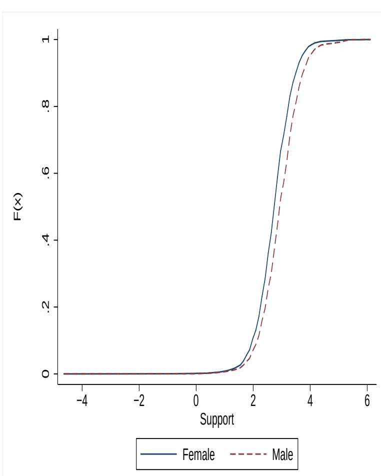
(d) 2005



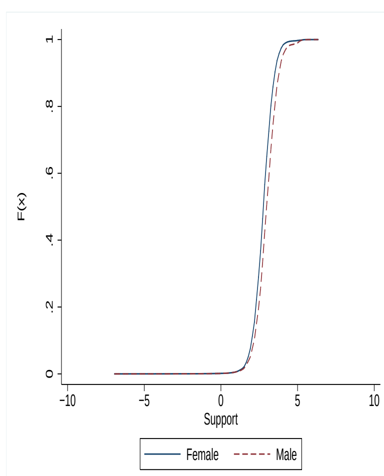
(e) 2006



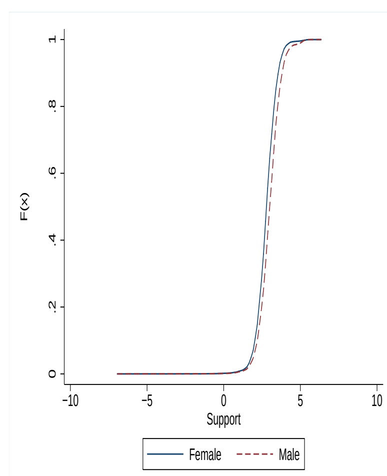
(f) 2007



(g) 2008

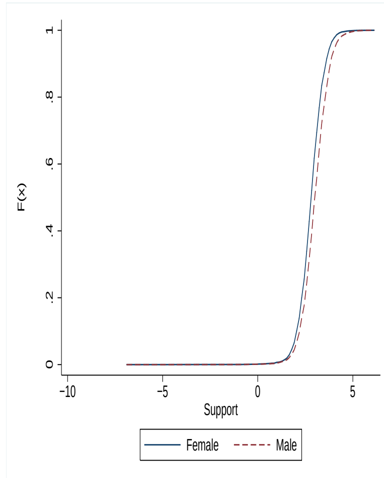


(h) 2009



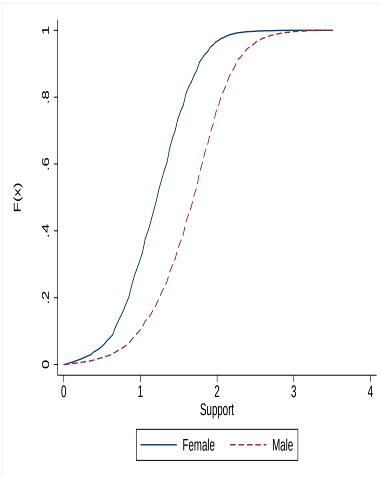
(i) 2010

Figure 5: CDF Comparisons of Female and Male Wage Distributions (2002 - 2010)

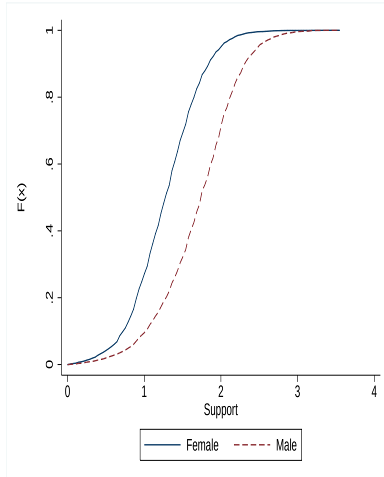


(a) 2011

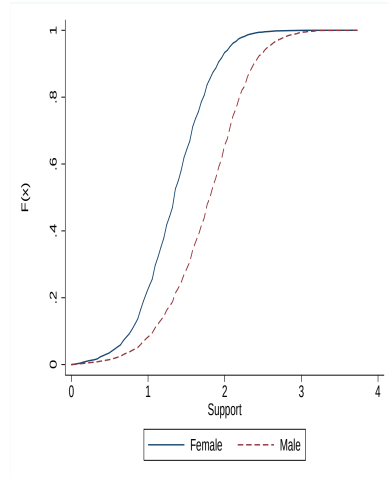
Figure 6: CDF Comparisons of Female and Male Wage Distributions (2011)



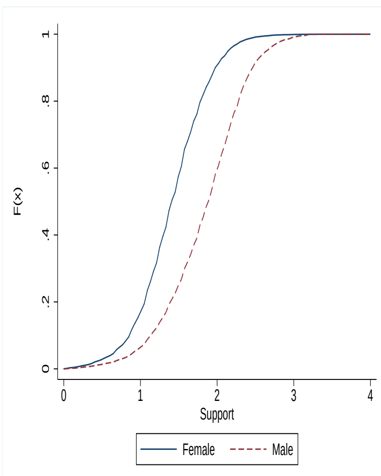
(a) 1976



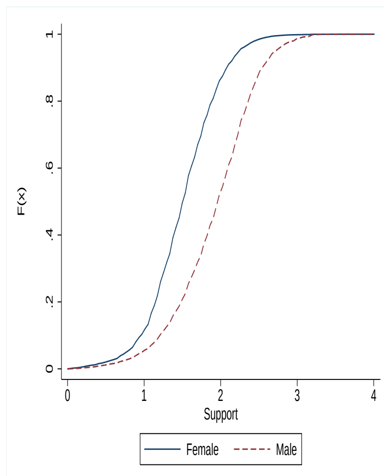
(b) 1977



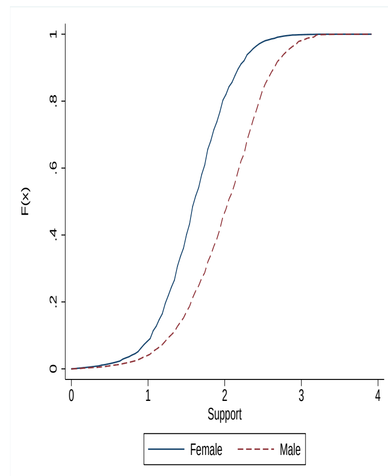
(c) 1978



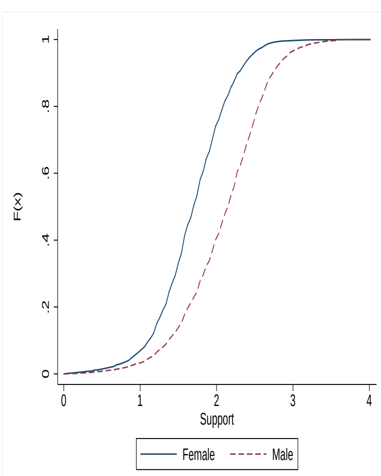
(d) 1979



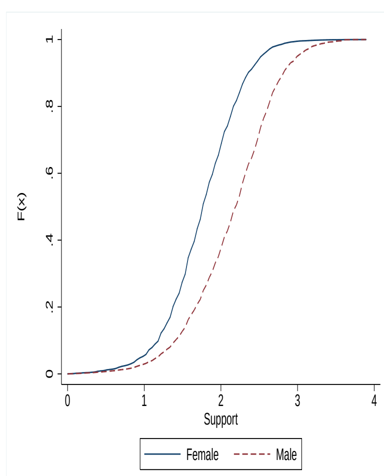
(e) 1980



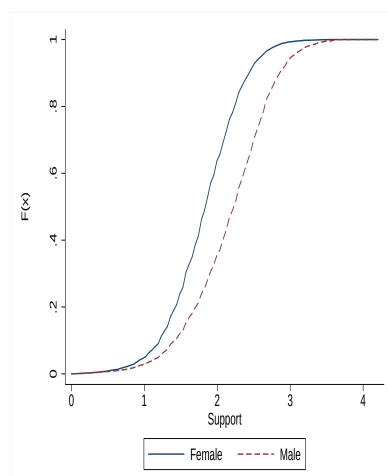
(f) 1981



(g) 1982

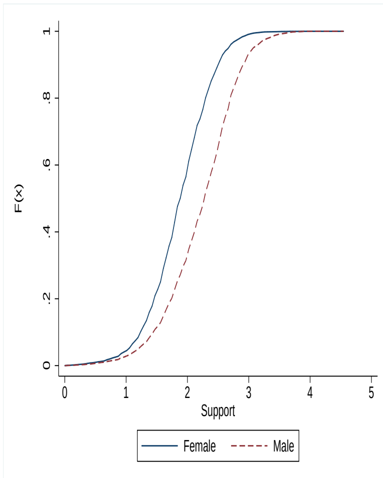


(h) 1983

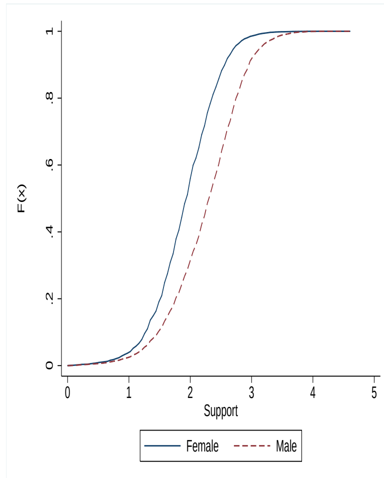


(i) 1984

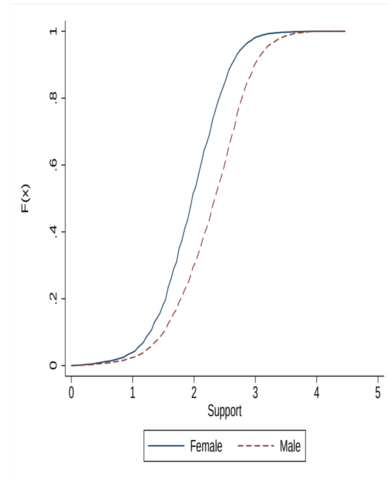
Figure 7: CDF Comparisons of Female and Male Wage Distributions (1976-1984)



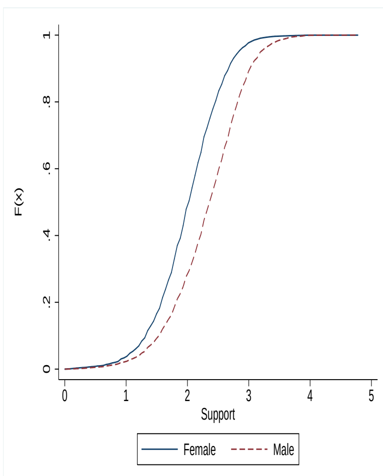
(a) 1985



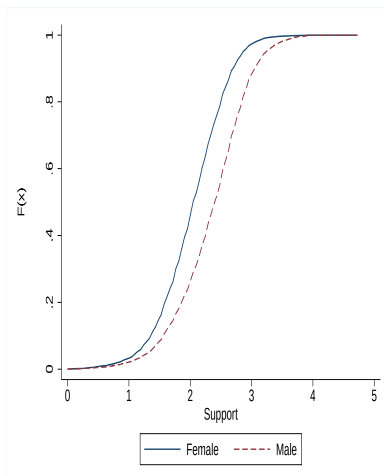
(b) 1986



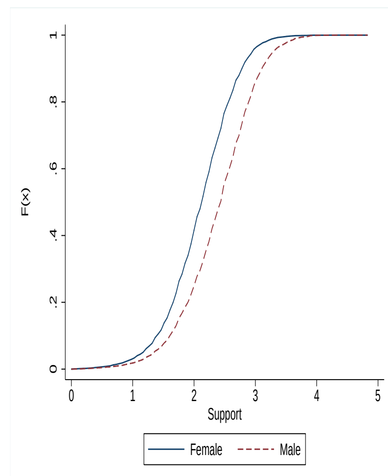
(c) 1987



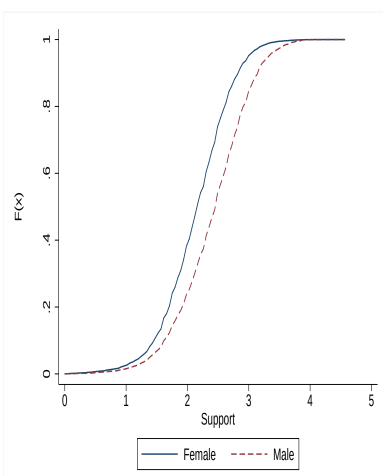
(d) 1988



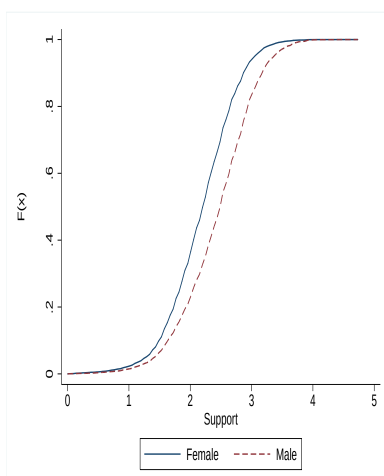
(e) 1989



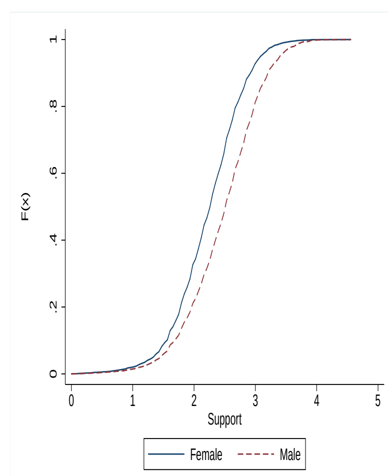
(f) 1990



(g) 1991

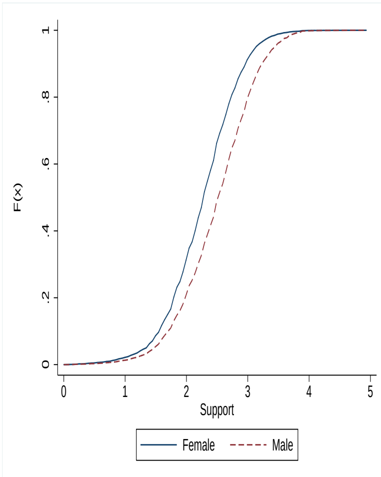


(h) 1992

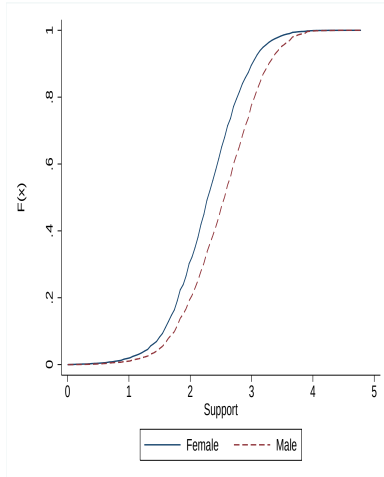


(i) 1993

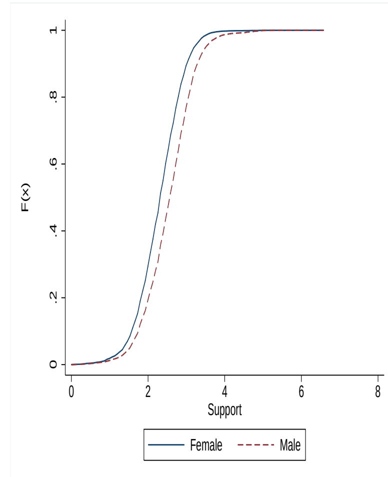
Figure 8: CDF Comparisons of Female and Male Wage Distributions (1985 - 1993)



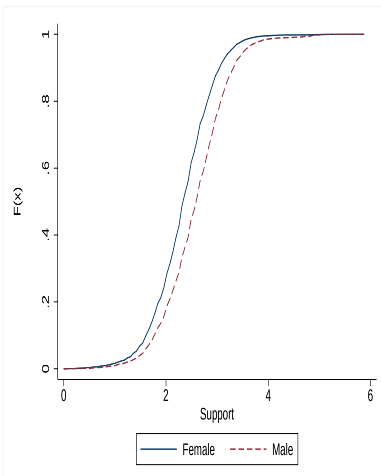
(a) 1994



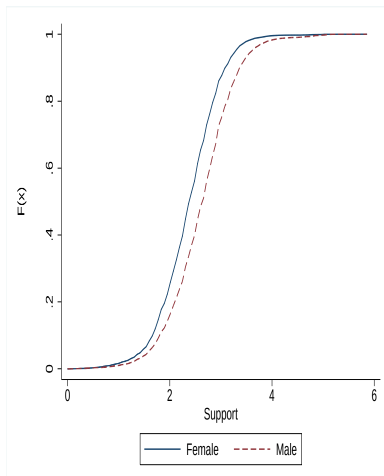
(b) 1995



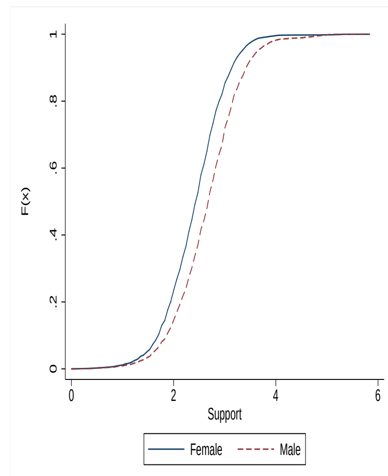
(c) 1996



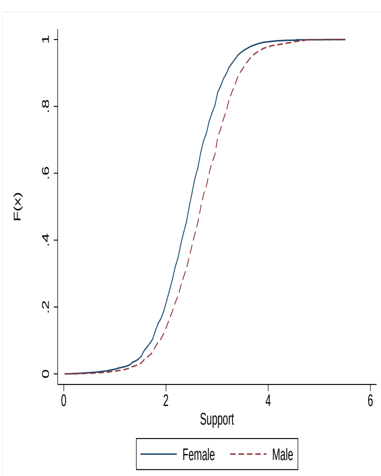
(d) 1997



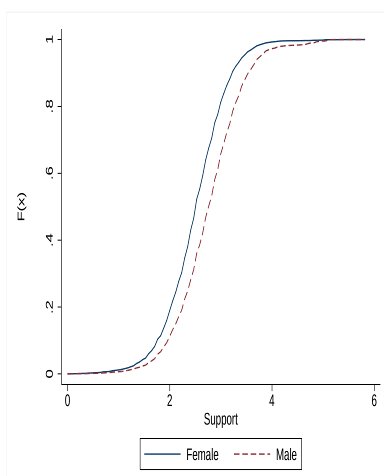
(e) 1998



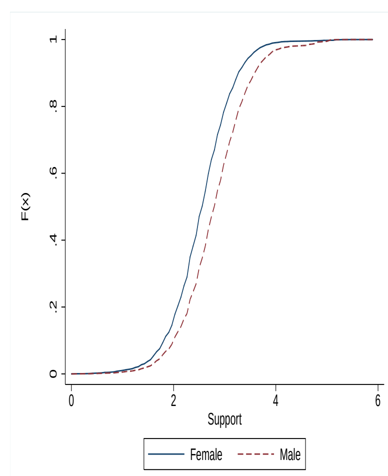
(f) 1999



(g) 2000

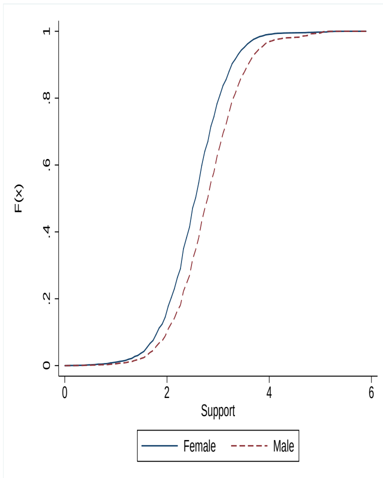


(h) 2001

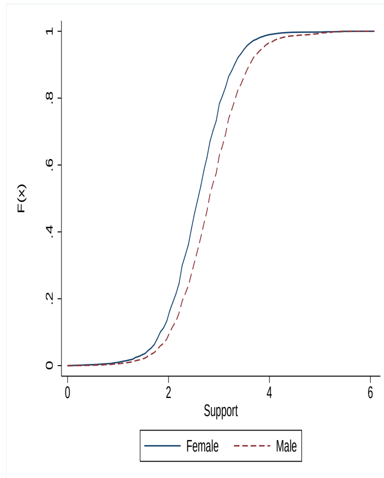


(i) 2002

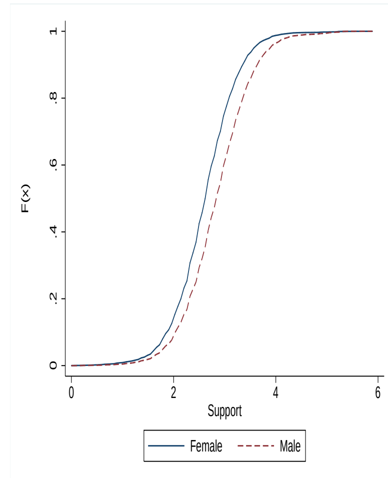
Figure 9: CDF Comparisons of Female and Male Wage Distributions (1994 - 2002)



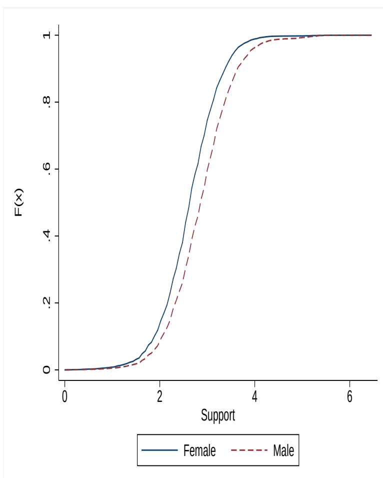
(a) 2002



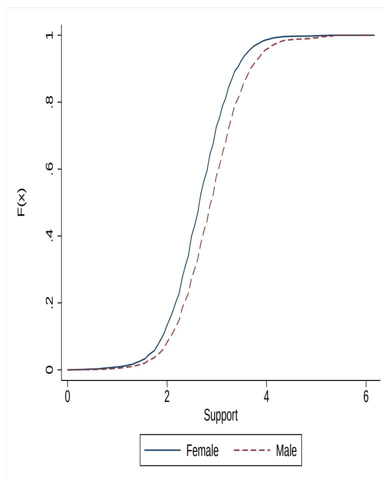
(b) 2003



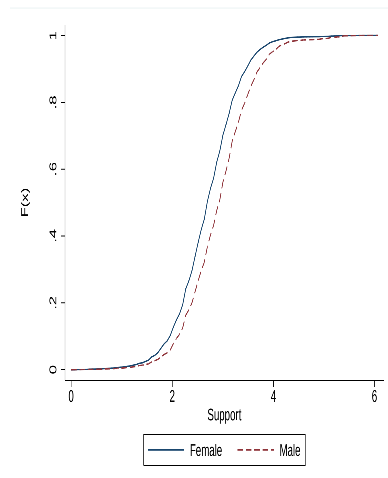
(c) 2004



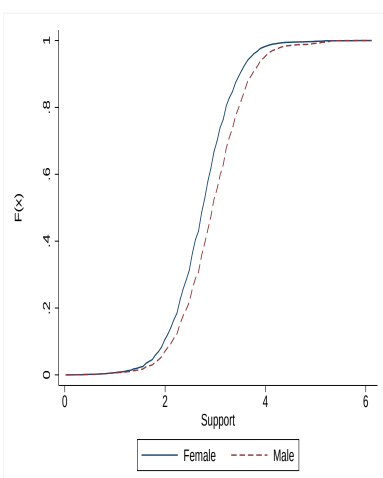
(d) 2005



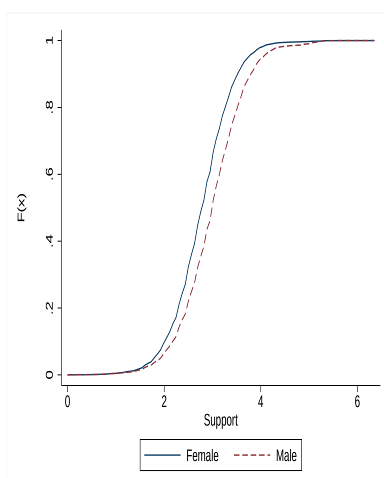
(e) 2006



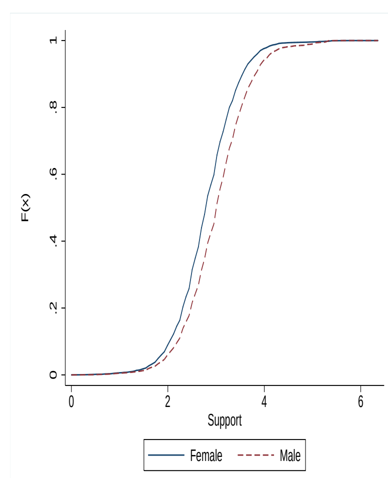
(f) 2007



(g) 2008

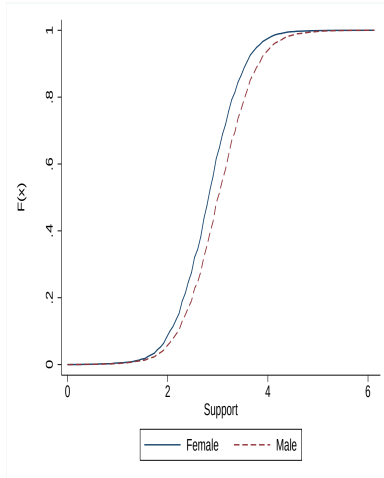


(h) 2009



(i) 2010

Figure 10: CDF Comparisons of Female and Male Wage Distributions (2002 - 2010)



(a) 2011

Figure 11: CDF Comparisons of Female and Male Wage Distributions (2011)

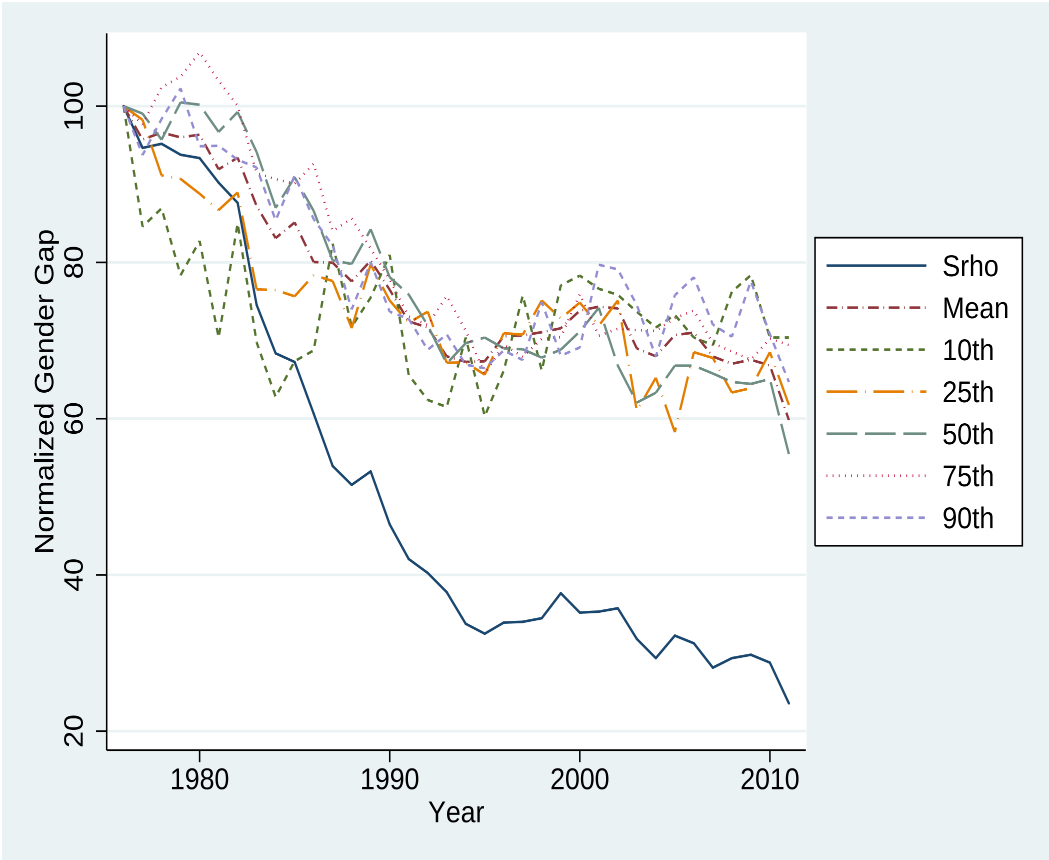
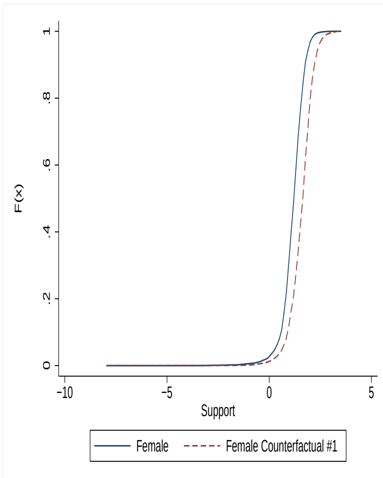
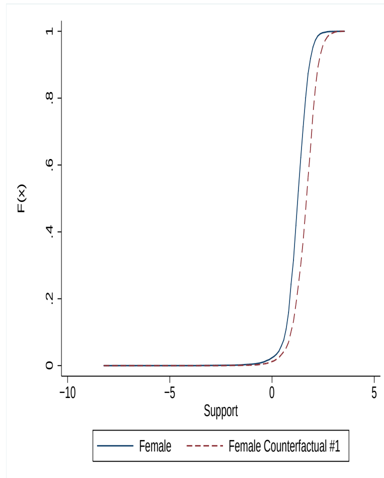


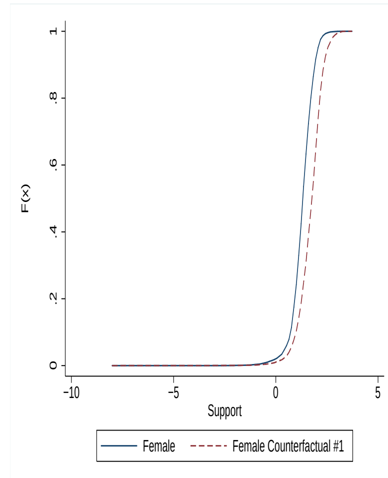
Figure 12: The Trend of the difference between the female wage distribution and the counterfactual distribution #1



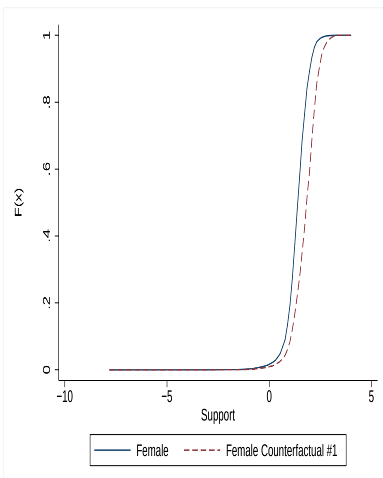
(a) 1976



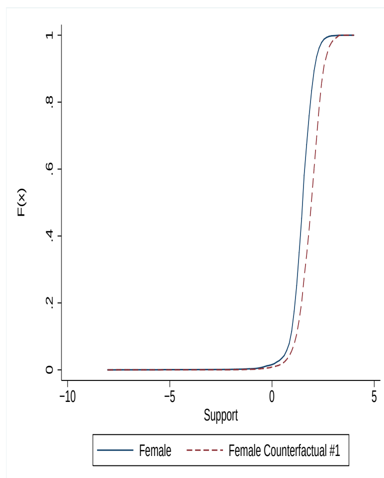
(b) 1977



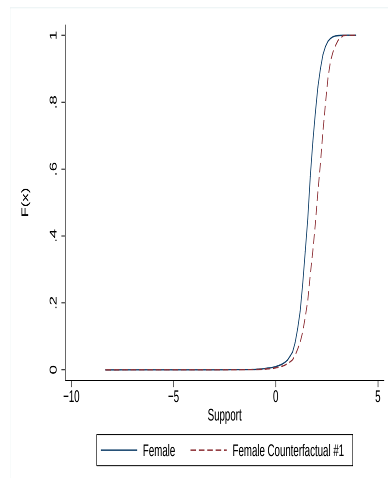
(c) 1978



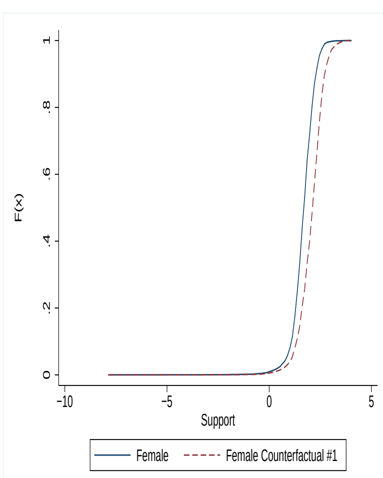
(d) 1979



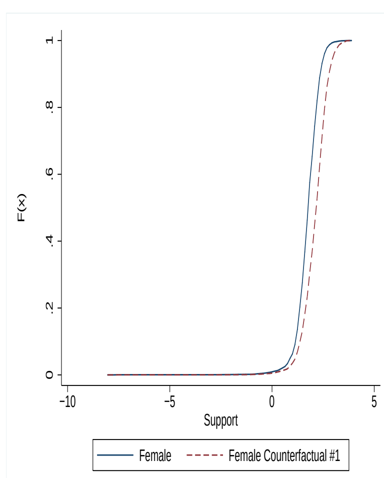
(e) 1980



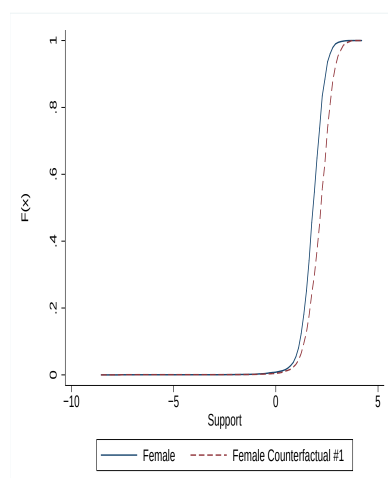
(f) 1981



(g) 1982

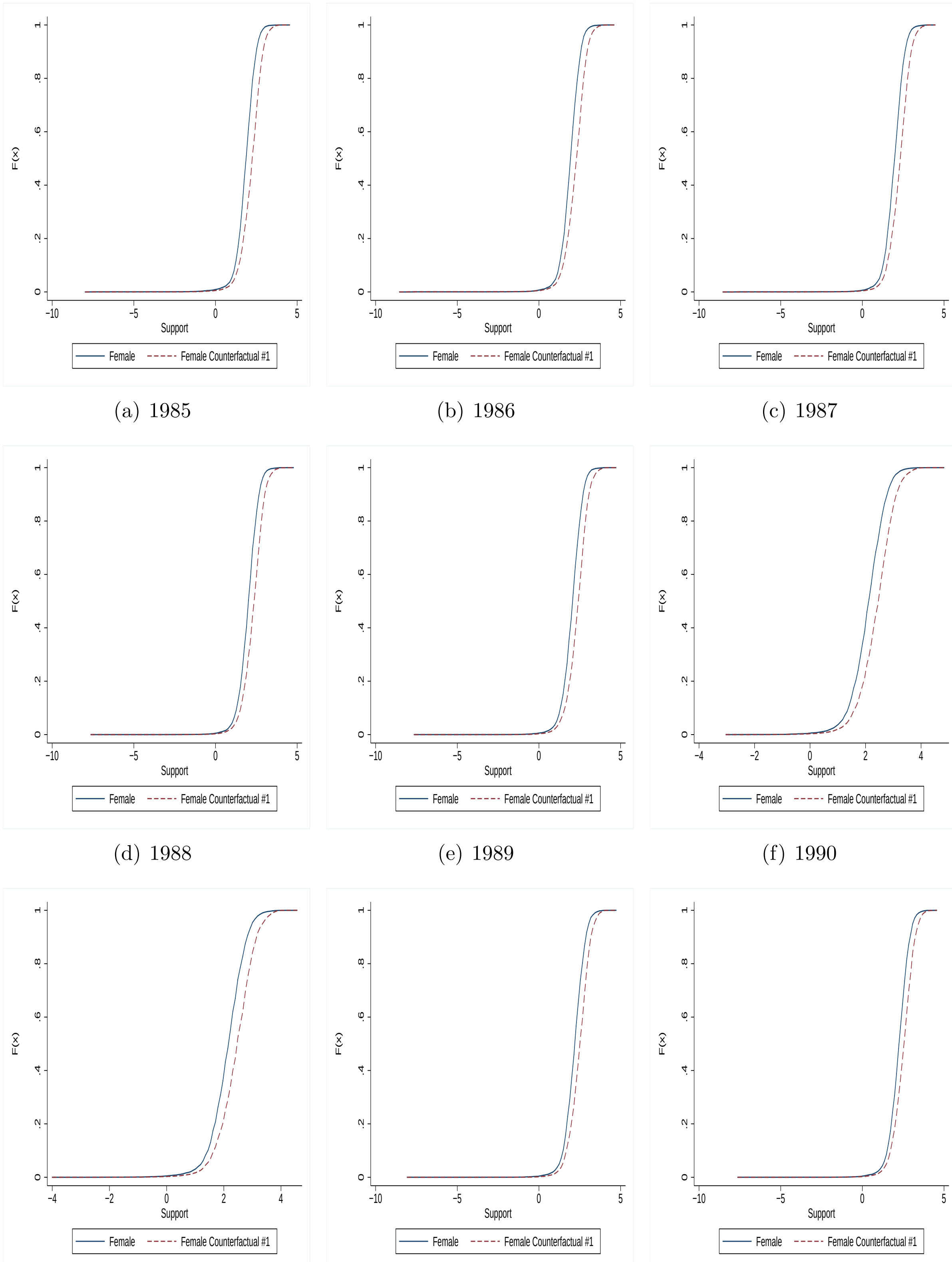


(h) 1983



(i) 1984

Figure 13: CDF Comparisons of Female and Female Counterfactual #1 Wage Distributions (1976-1984)



(a) 1985

(b) 1986

(c) 1987

(d) 1988

(e) 1989

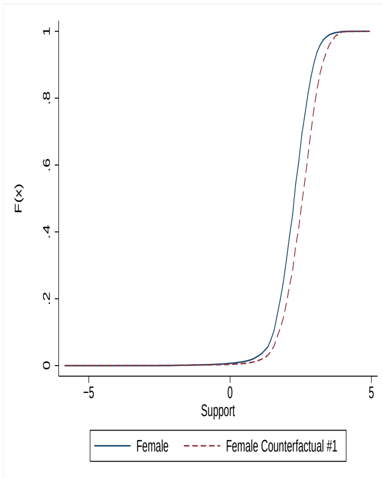
(f) 1990

(g) 1991

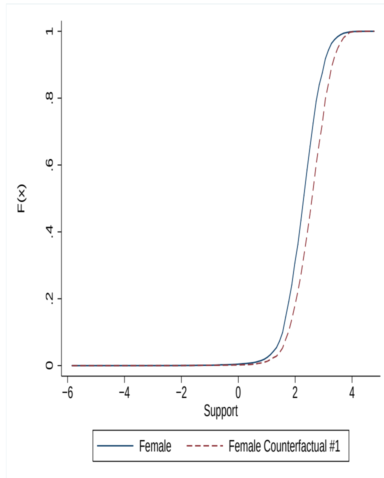
(h) 1992

(i) 1993

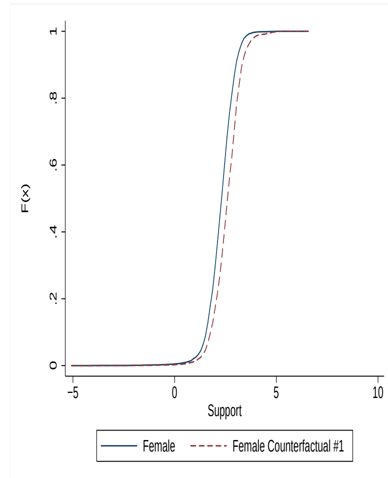
Figure 14: CDF Comparisons of Female and Female Counterfactual #1 Wage Distributions (1985 - 1993)



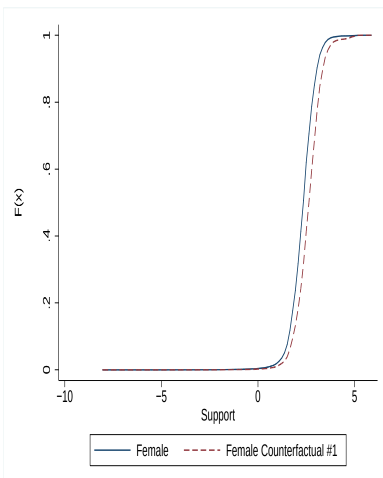
(a) 1994



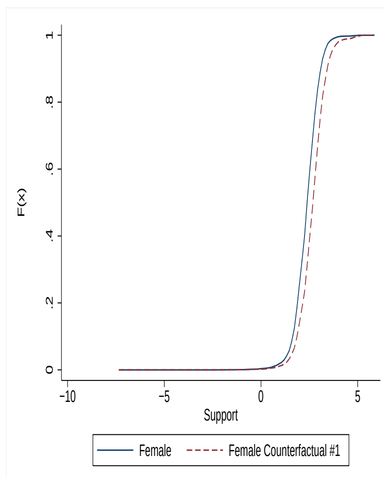
(b) 1995



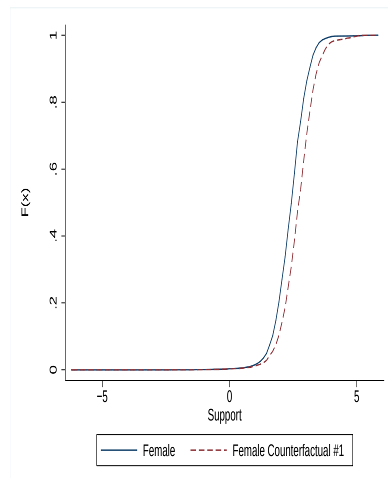
(c) 1996



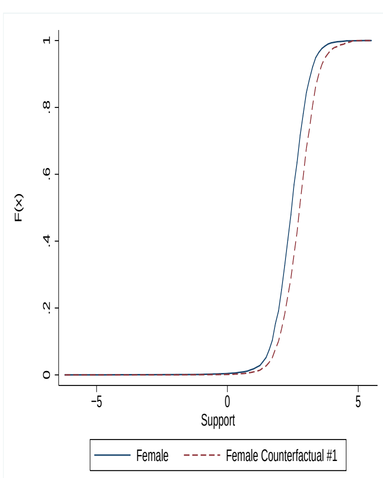
(d) 1997



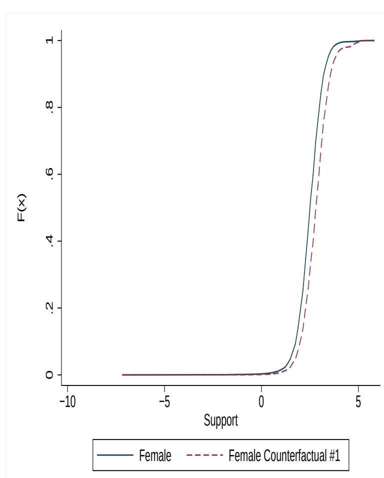
(e) 1998



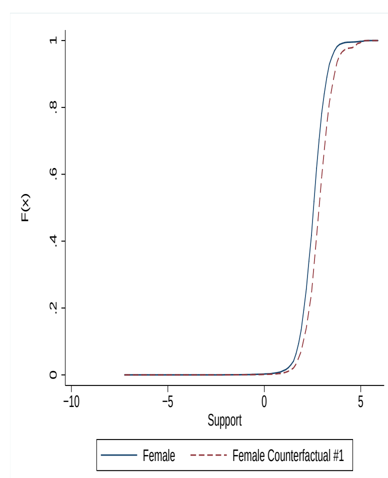
(f) 1999



(g) 2000

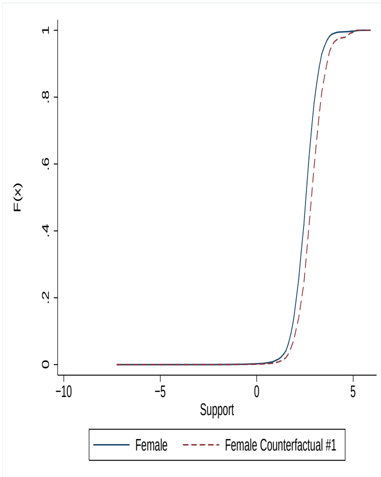


(h) 2001

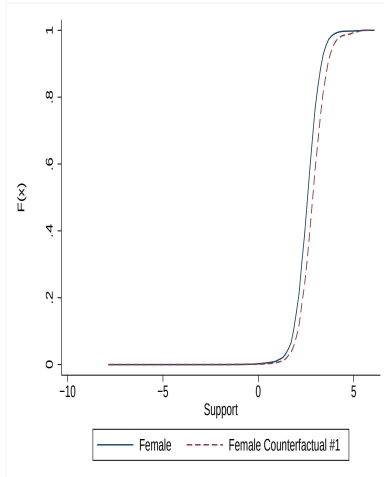


(i) 2002

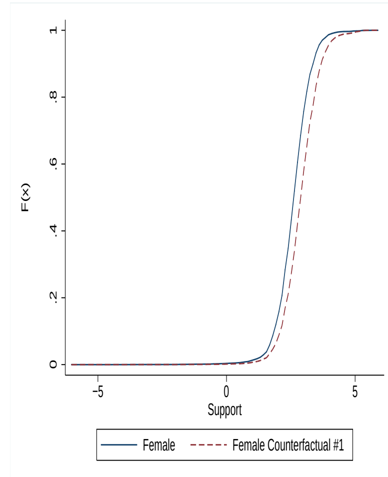
Figure 15: CDF Comparisons of Female and Female Counterfactual #1 Wage Distributions (1994 - 2002)



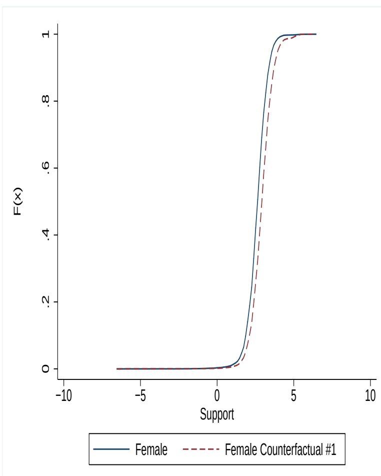
(a) 2002



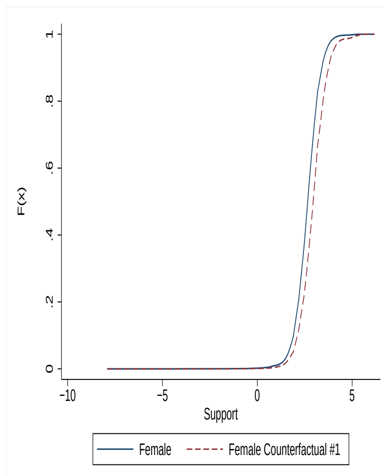
(b) 2003



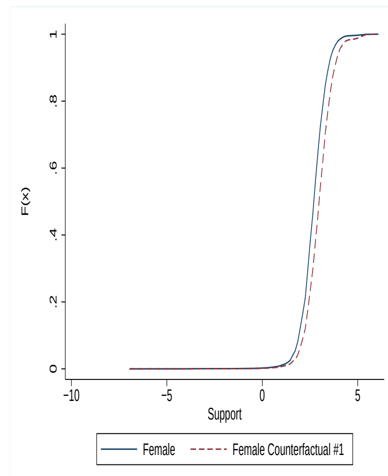
(c) 2004



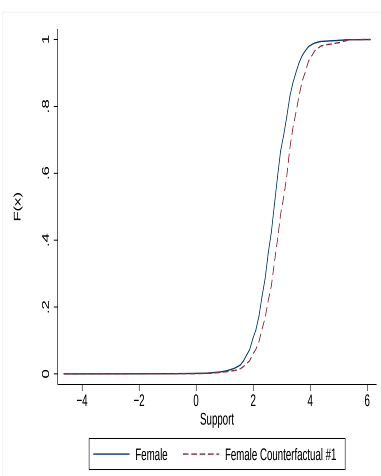
(d) 2005



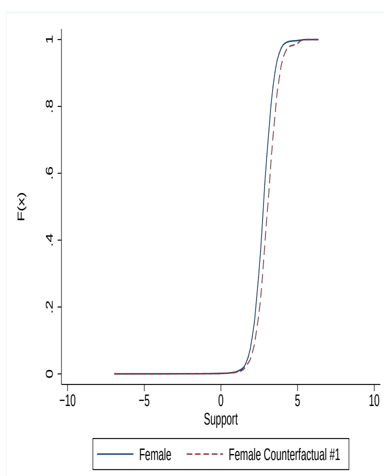
(e) 2006



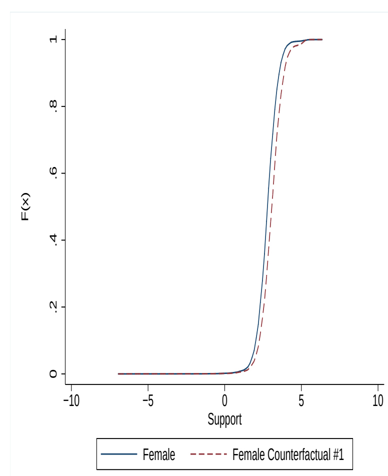
(f) 2007



(g) 2008

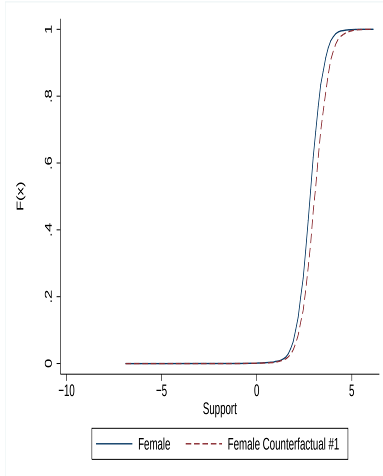


(h) 2009



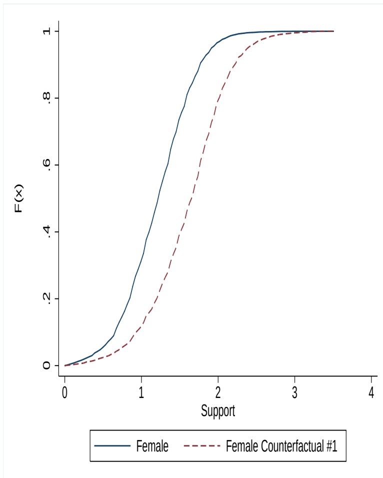
(i) 2010

Figure 16: CDF Comparisons of Female and Female Counterfactual #1 Wage Distributions (2002 - 2010)

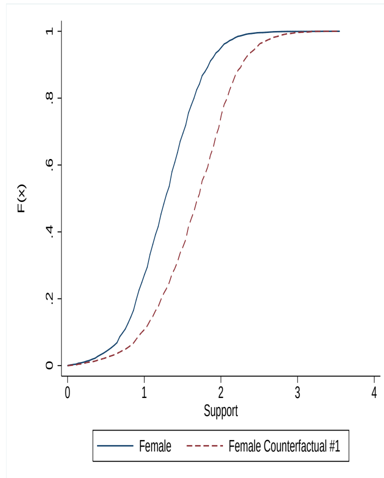


(a) 2011

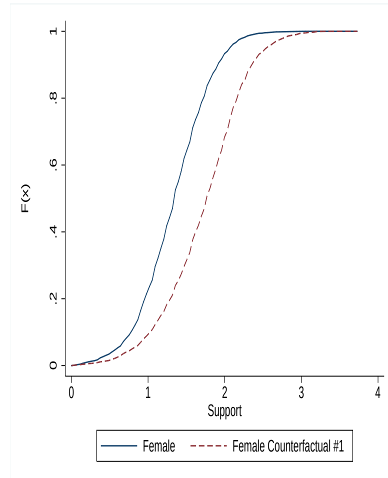
Figure 17: CDF Comparisons of Female and Female Counterfactual #1 Wage Distributions (2011)



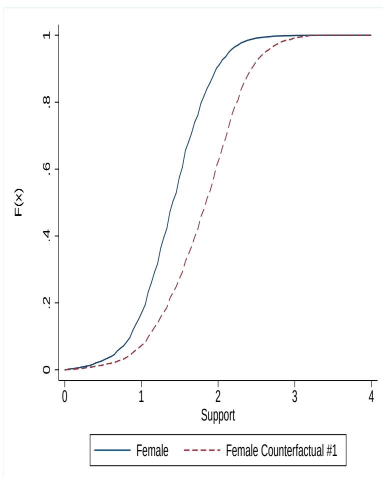
(a) 1976



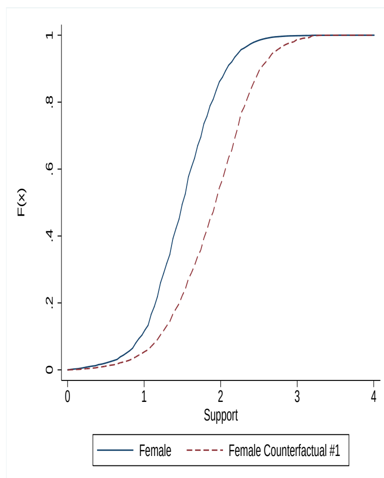
(b) 1977



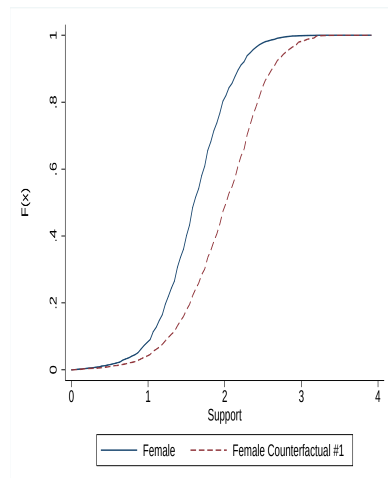
(c) 1978



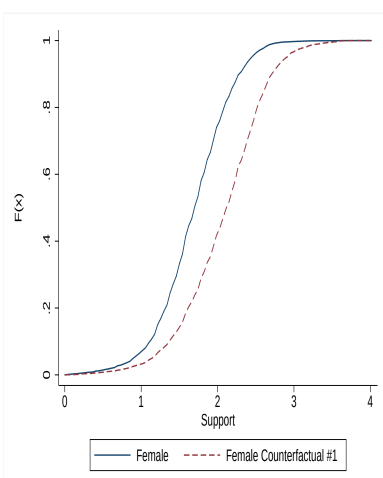
(d) 1979



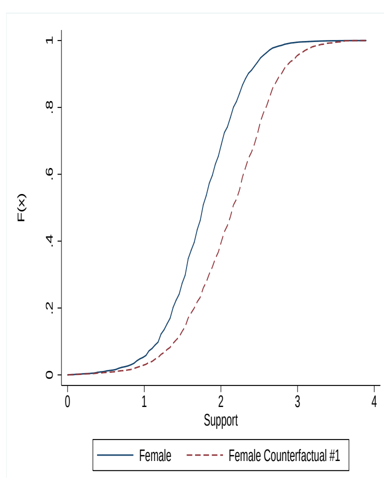
(e) 1980



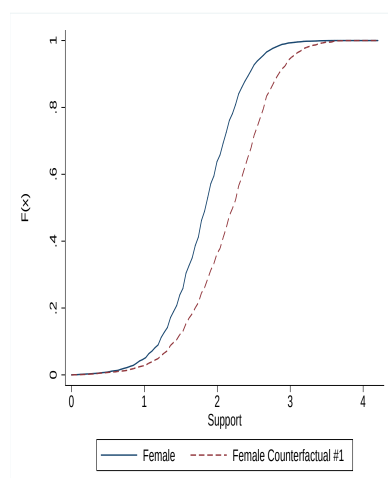
(f) 1981



(g) 1982

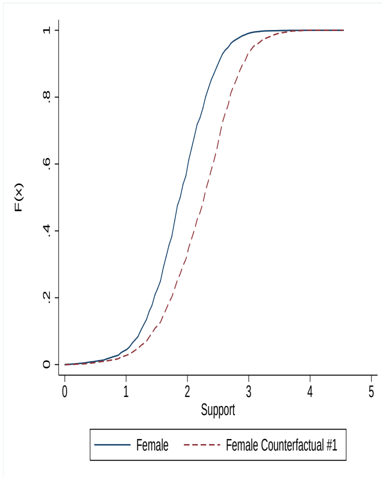


(h) 1983

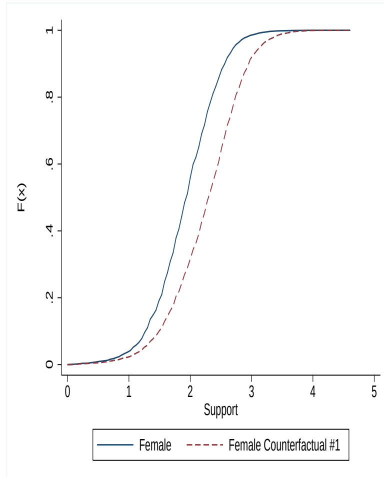


(i) 1984

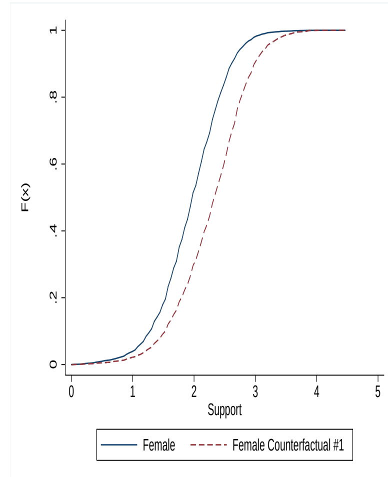
Figure 18: CDF Comparisons of Female and Female Counterfactual #1 Wage Distributions (1976-1984)



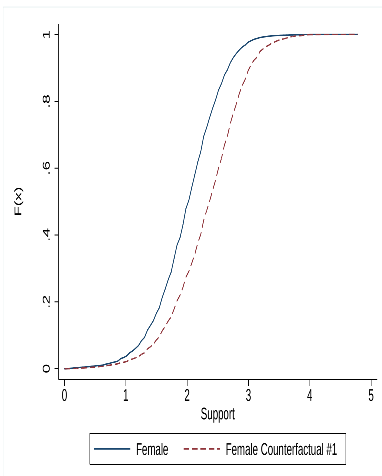
(a) 1985



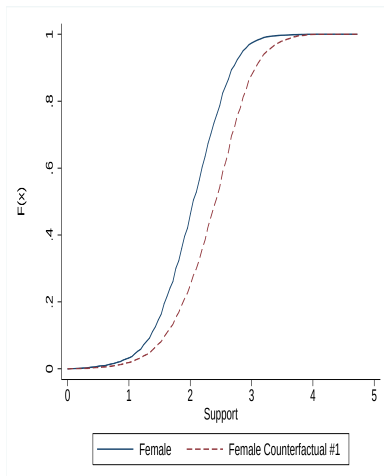
(b) 1986



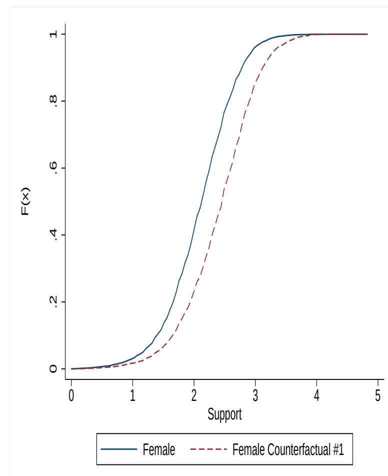
(c) 1987



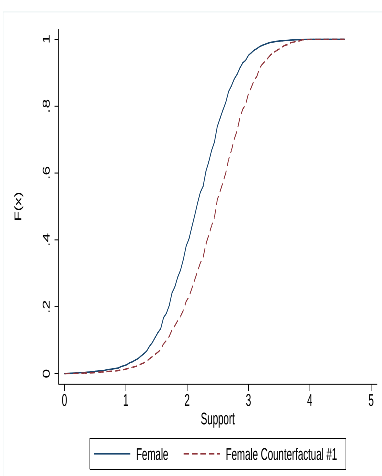
(d) 1988



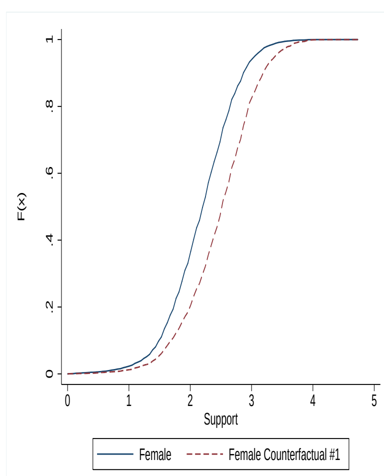
(e) 1989



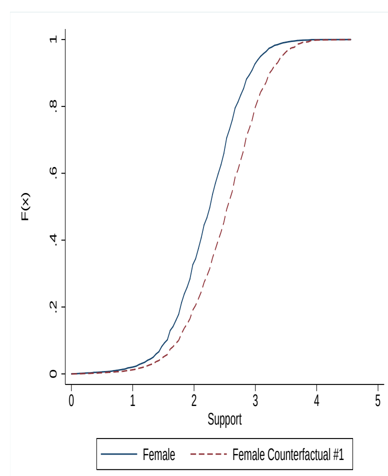
(f) 1990



(g) 1991

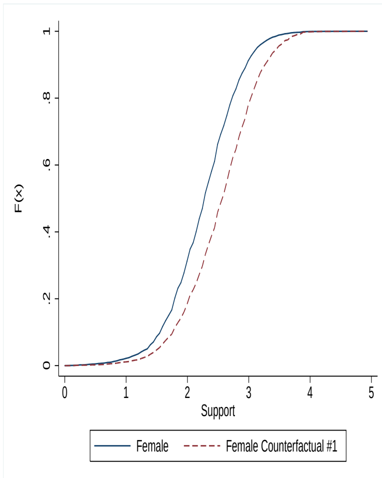


(h) 1992

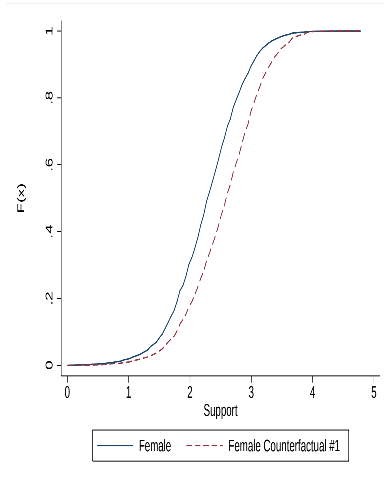


(i) 1993

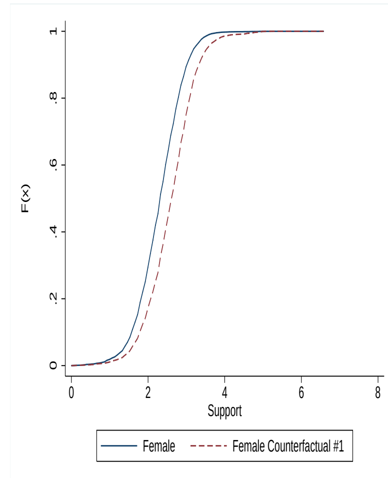
Figure 19: CDF Comparisons of Female and Female Counterfactual #1 Wage Distributions (1985 - 1993)



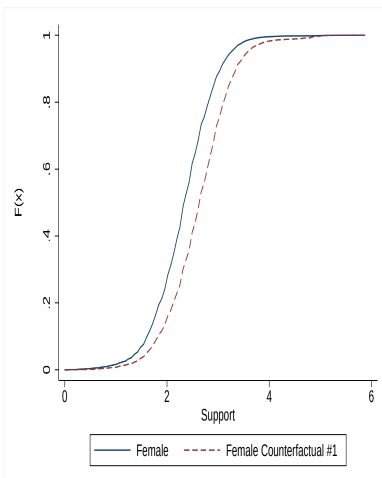
(a) 1994



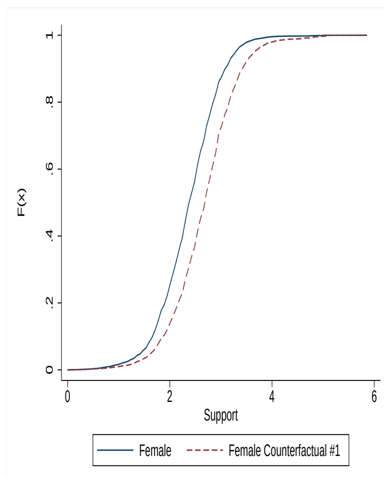
(b) 1995



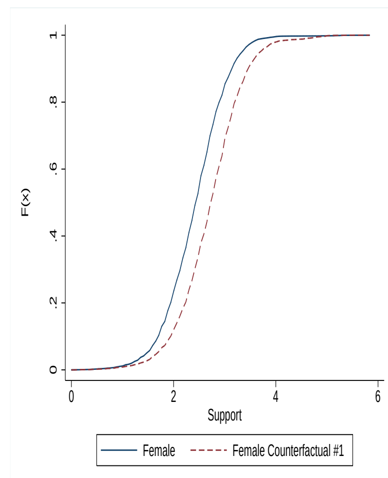
(c) 1996



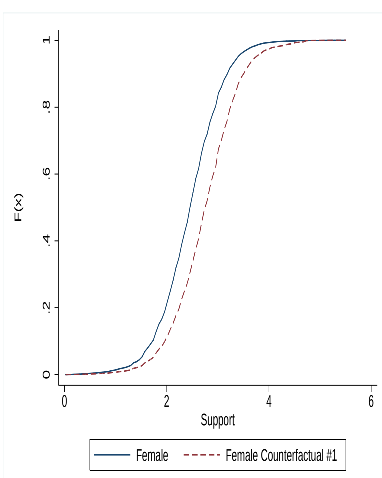
(d) 1997



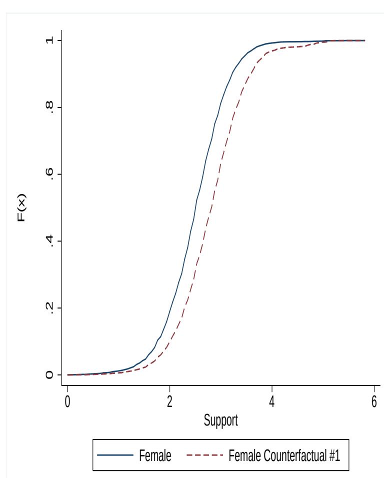
(e) 1998



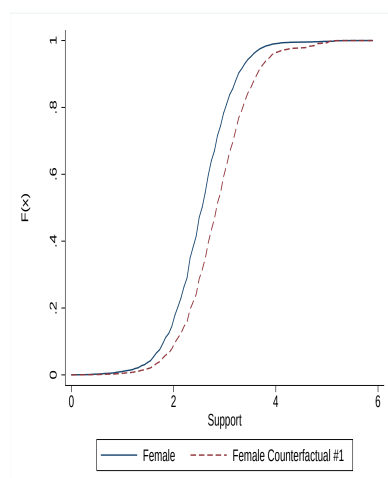
(f) 1999



(g) 2000

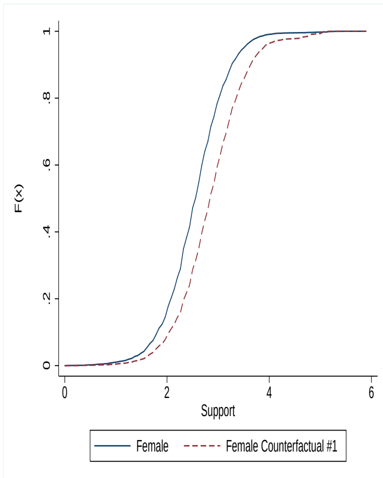


(h) 2001

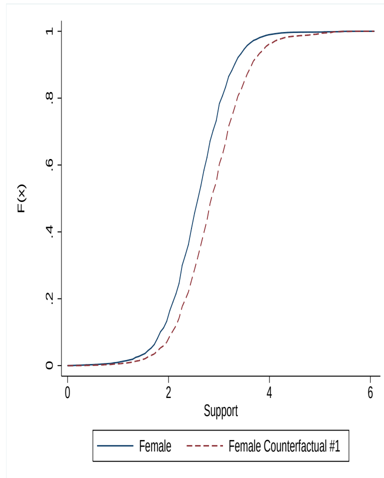


(i) 2002

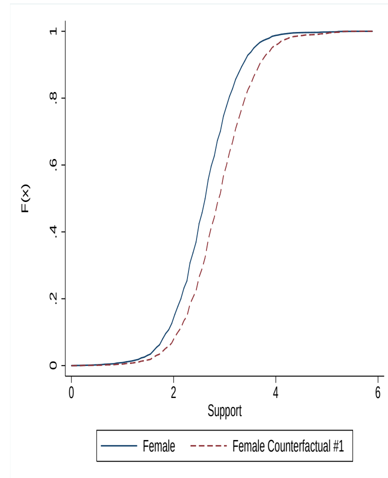
Figure 20: CDF Comparisons of Female and Female Counterfactual #1 Wage Distributions (1994 - 2002)



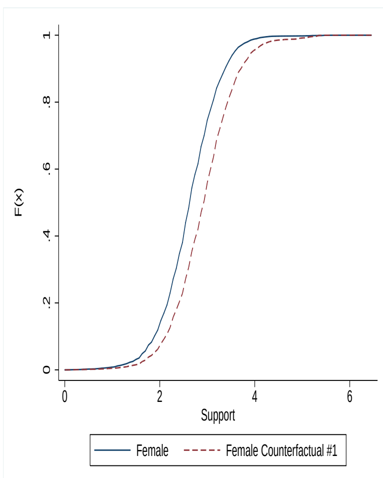
(a) 2002



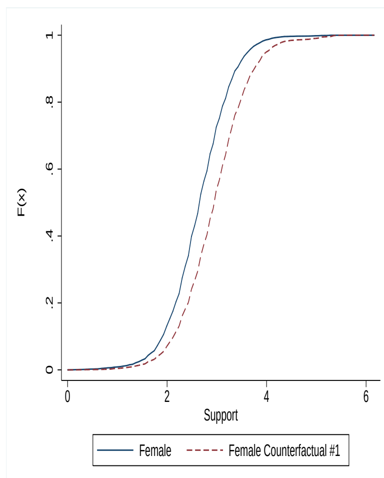
(b) 2003



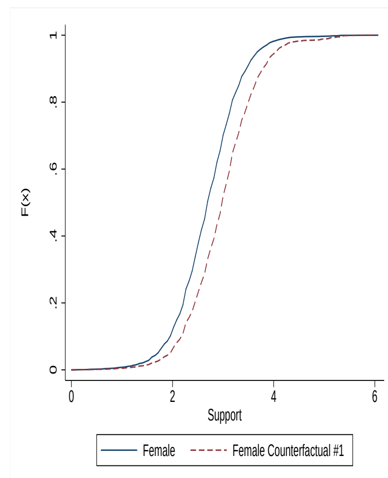
(c) 2004



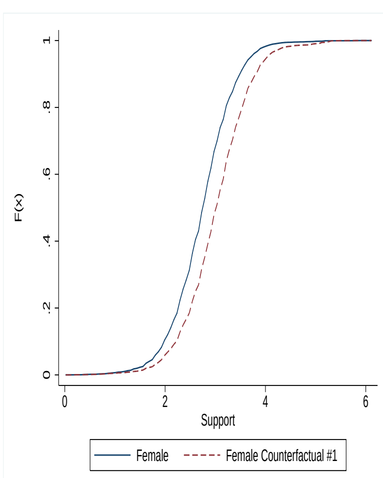
(d) 2005



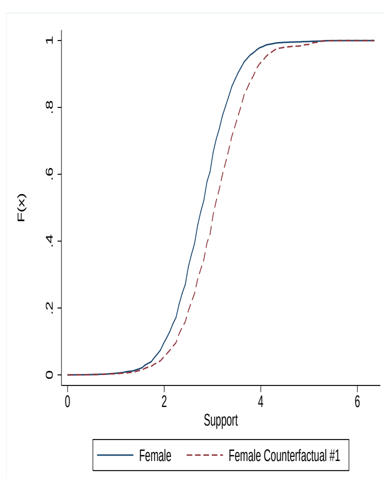
(e) 2006



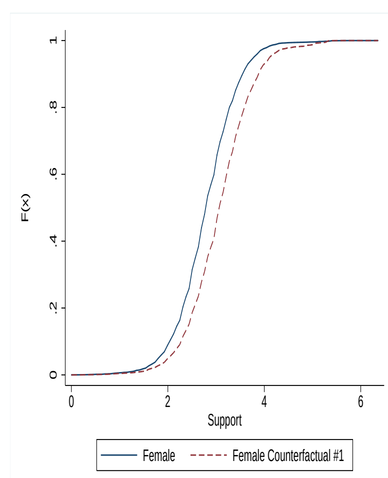
(f) 2007



(g) 2008

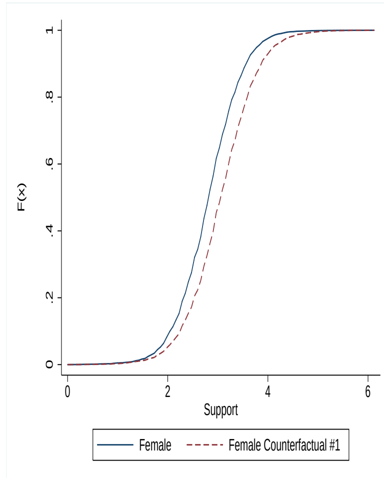


(h) 2009



(i) 2010

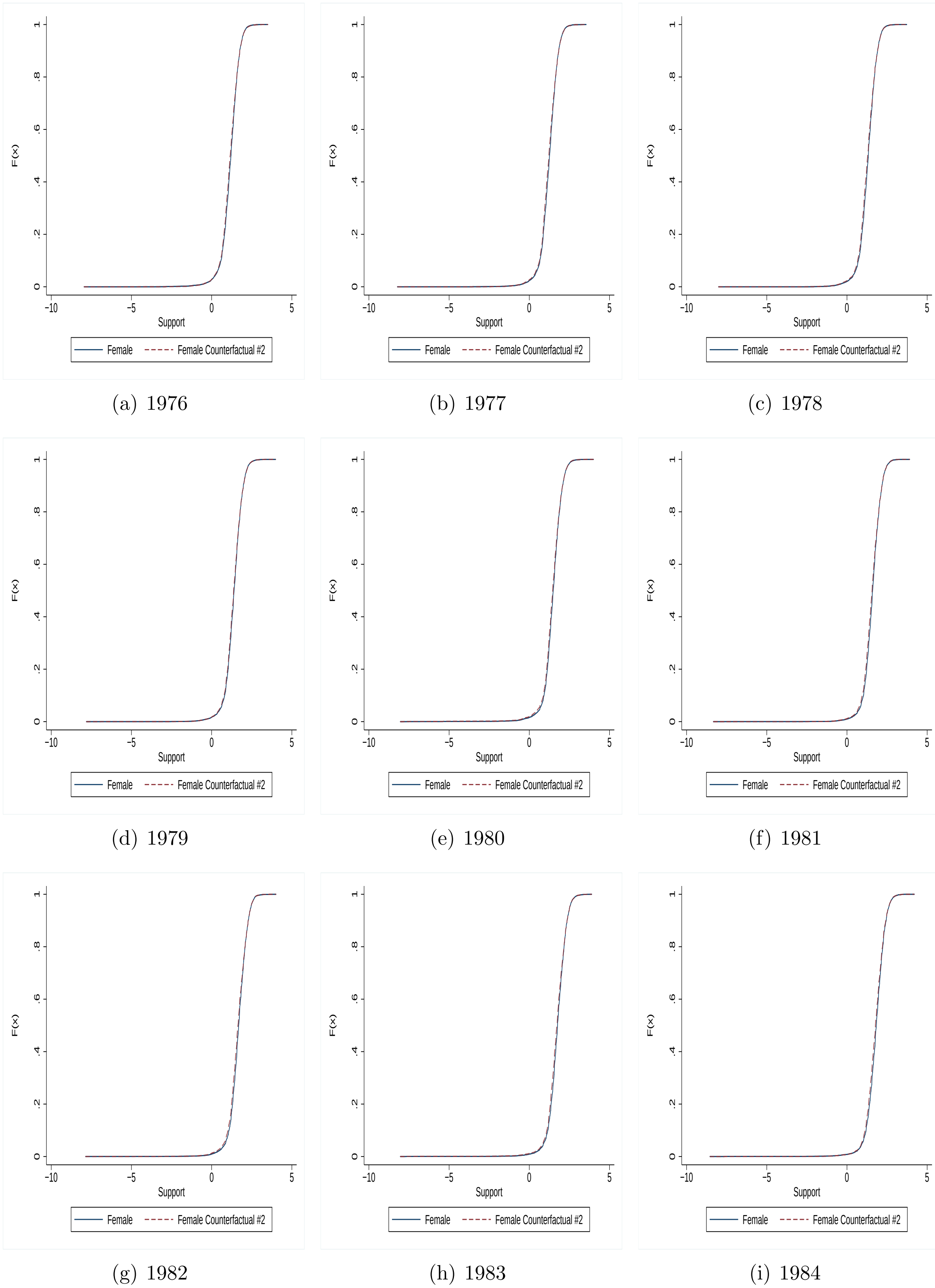
Figure 21: CDF Comparisons of Female and Female Counterfactual #1 Wage Distributions (2002 - 2010)



(a) 2011

Figure 22: CDF Comparisons of Female and Female Counterfactual #1 Wage Distributions (2011)

Figure 23: The Trend of the difference between the female wage distribution and the counterfactual distribution #2

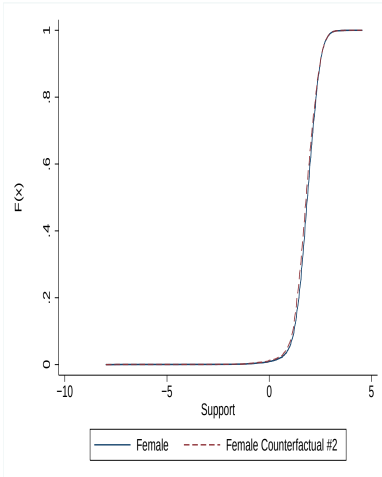


(a) 1976 (b) 1977 (c) 1978

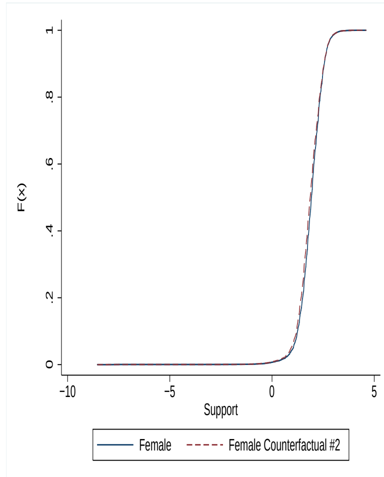
(d) 1979 (e) 1980 (f) 1981

(g) 1982 (h) 1983 (i) 1984

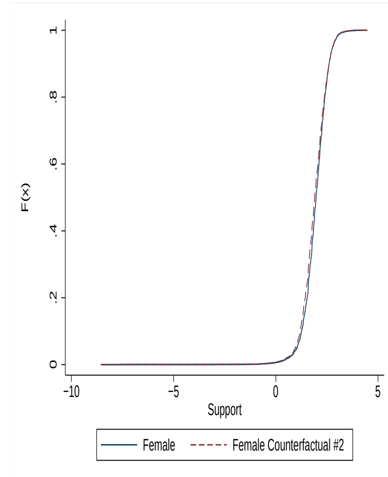
Figure 24: CDF Comparisons of Female and Female Counterfactual #2 Wage Distributions (1976-1984)



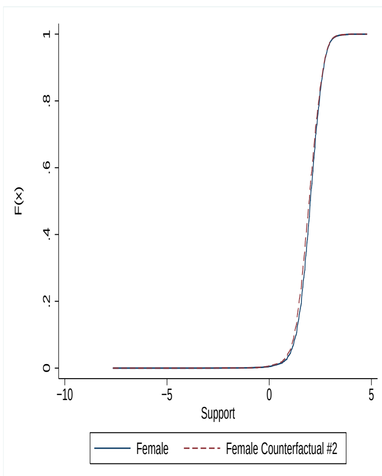
(a) 1985



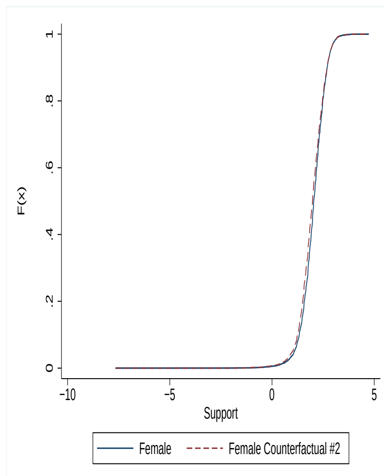
(b) 1986



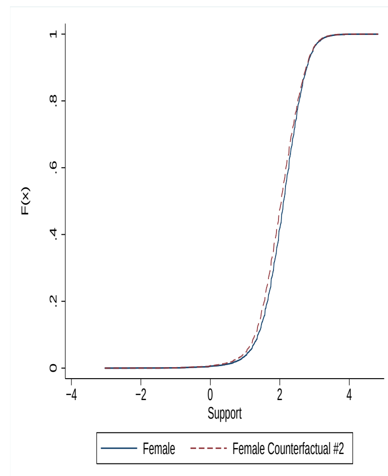
(c) 1987



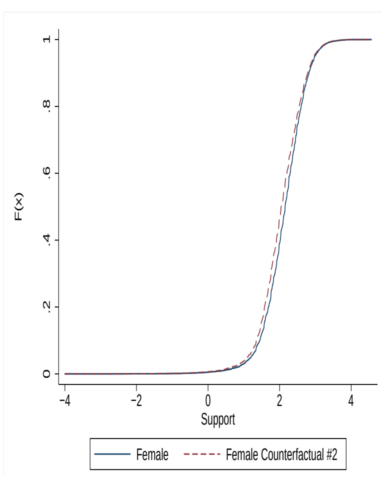
(d) 1988



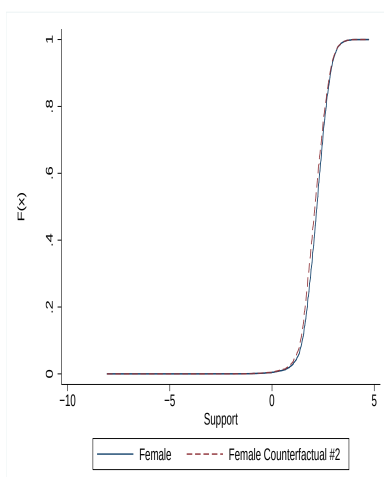
(e) 1989



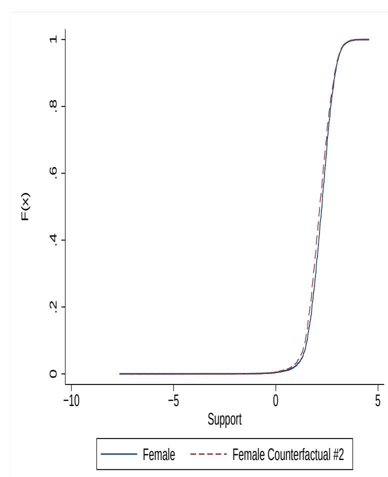
(f) 1990



(g) 1991

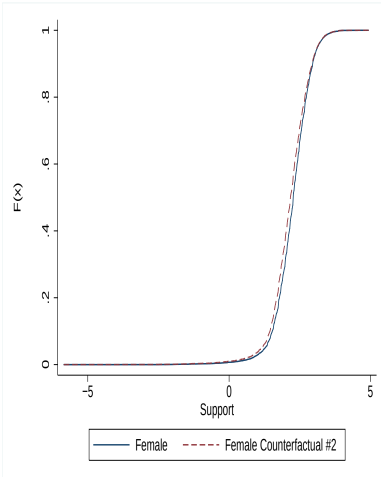


(h) 1992

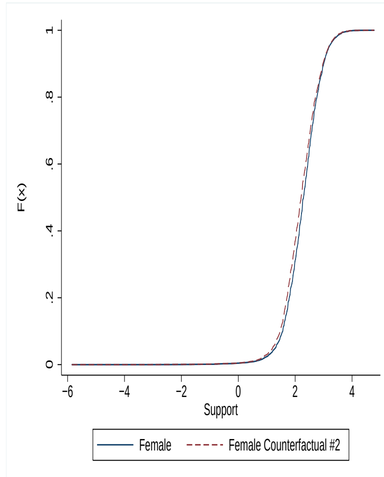


(i) 1993

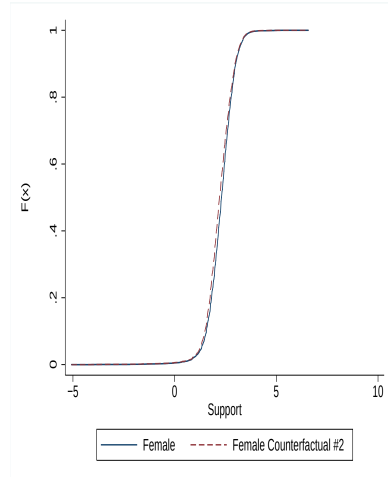
Figure 25: CDF Comparisons of Female and Female Counterfactual #2 Wage Distributions (1985 - 1993)



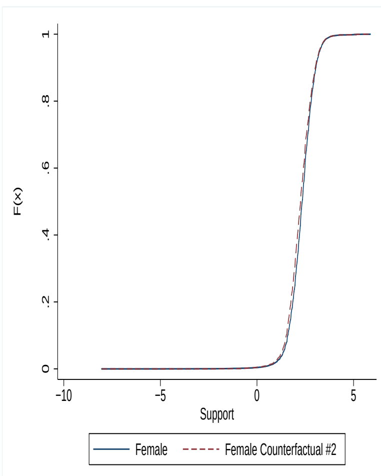
(a) 1994



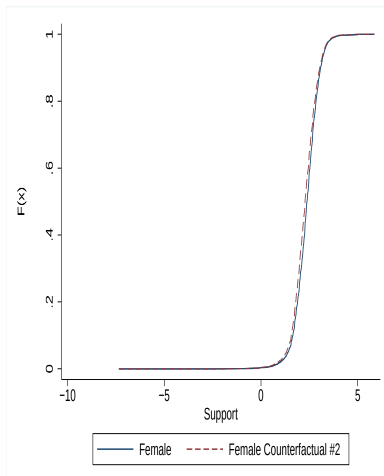
(b) 1995



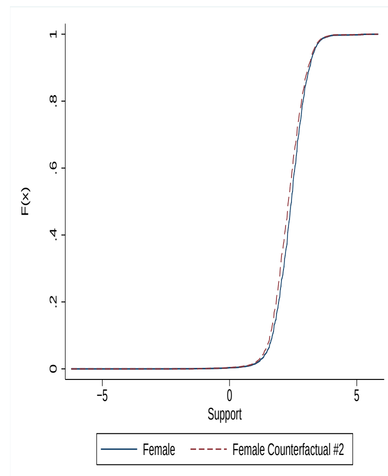
(c) 1996



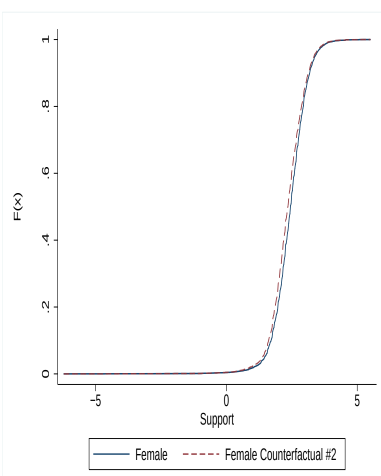
(d) 1997



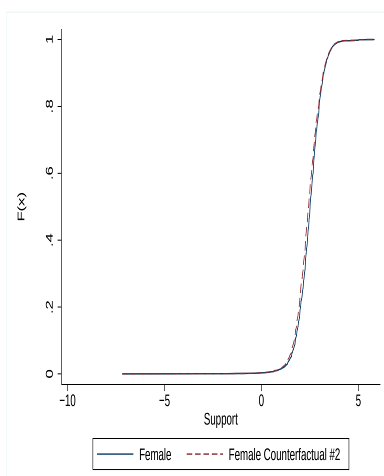
(e) 1998



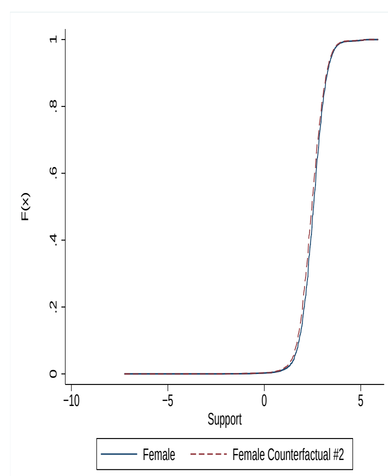
(f) 1999



(g) 2000

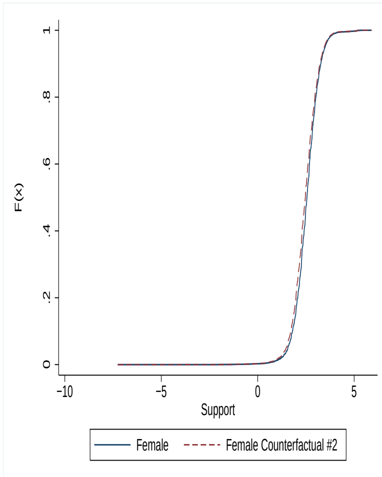


(h) 2001

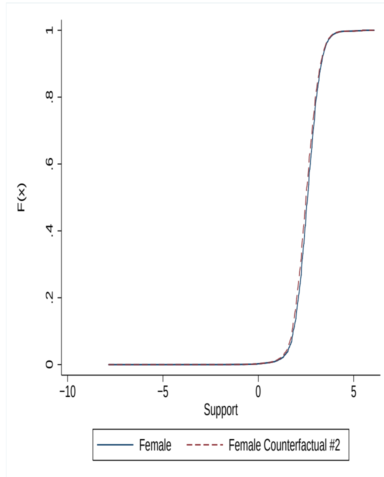


(i) 2002

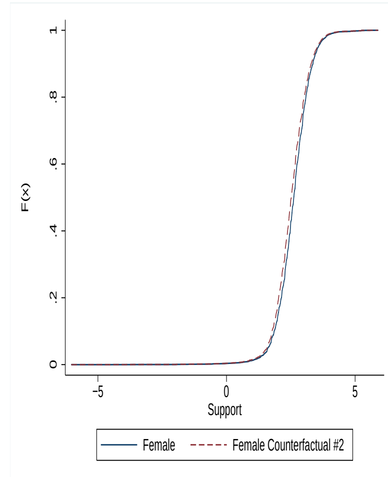
Figure 26: CDF Comparisons of Female and Female Counterfactual #2 Wage Distributions (1994 - 2002)



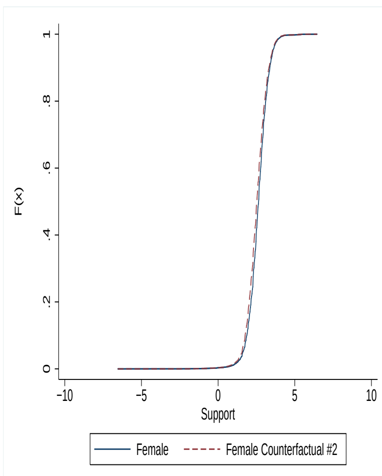
(a) 2002



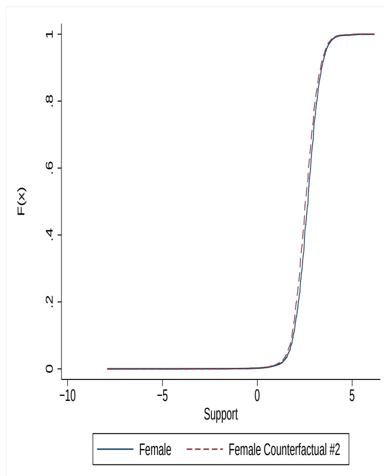
(b) 2003



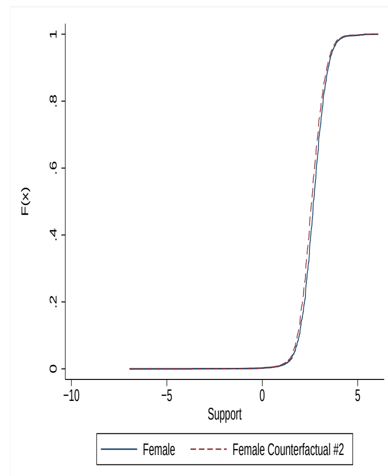
(c) 2004



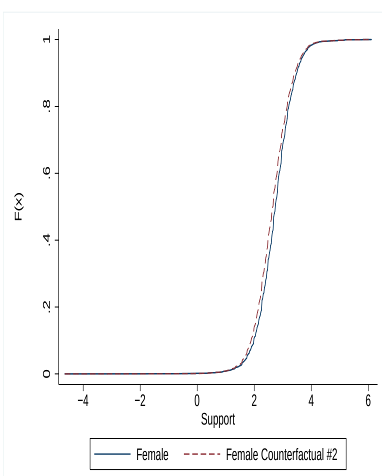
(d) 2005



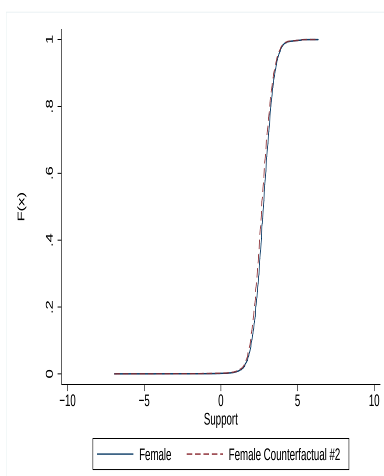
(e) 2006



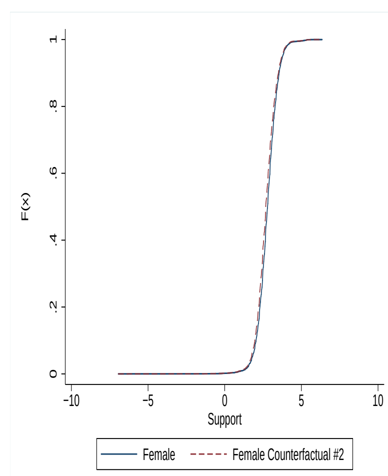
(f) 2007



(g) 2008

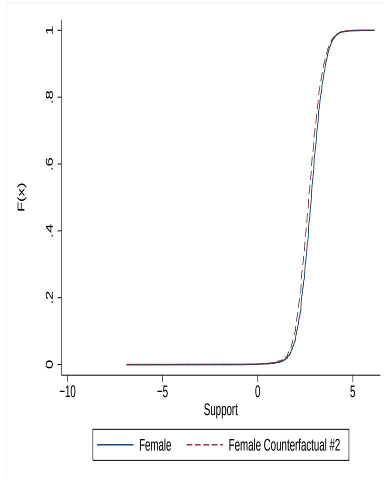


(h) 2009



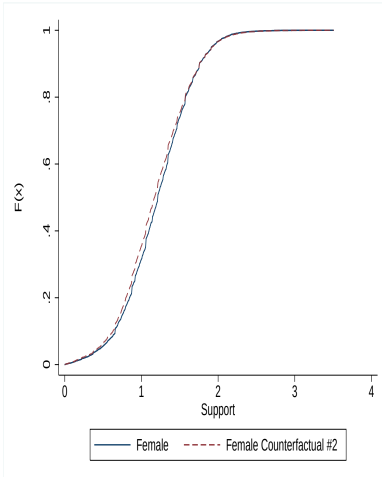
(i) 2010

Figure 27: CDF Comparisons of Female and Female Counterfactual #2 Wage Distributions (2002 - 2010)

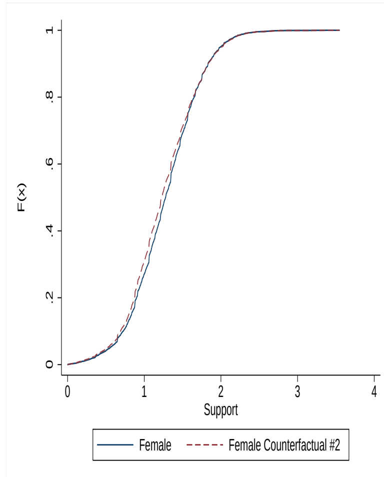


(a) 2011

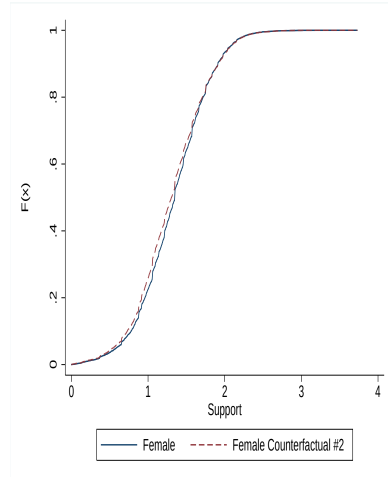
Figure 28: CDF Comparisons of Female and Female Counterfactual #2 Wage Distributions (2011)



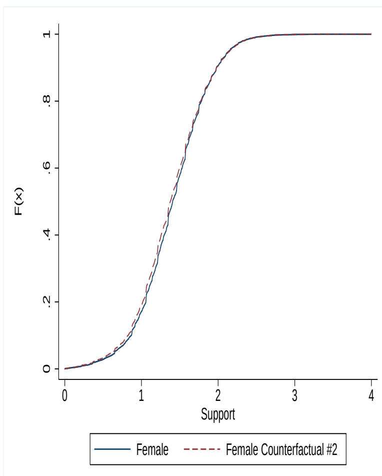
(a) 1976



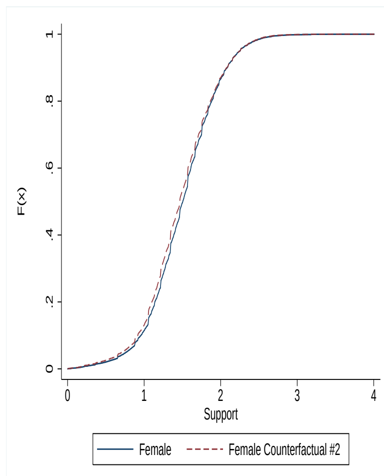
(b) 1977



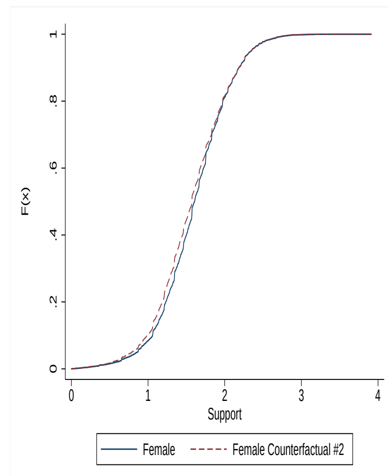
(c) 1978



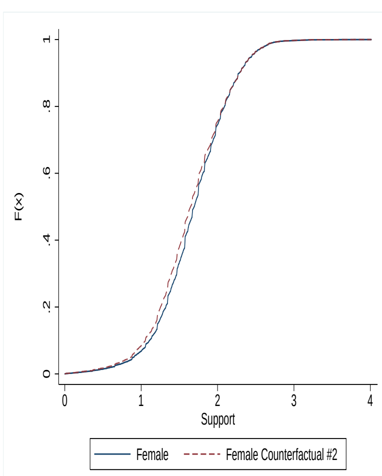
(d) 1979



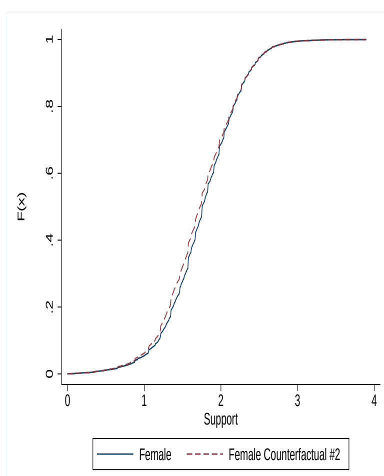
(e) 1980



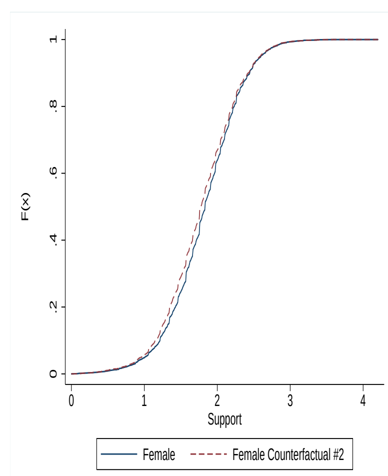
(f) 1981



(g) 1982

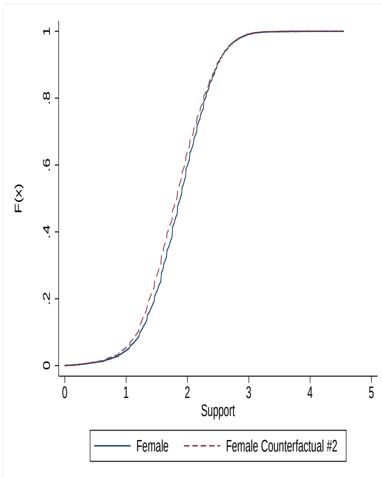


(h) 1983

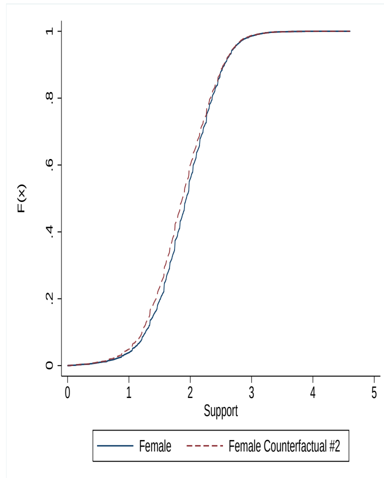


(i) 1984

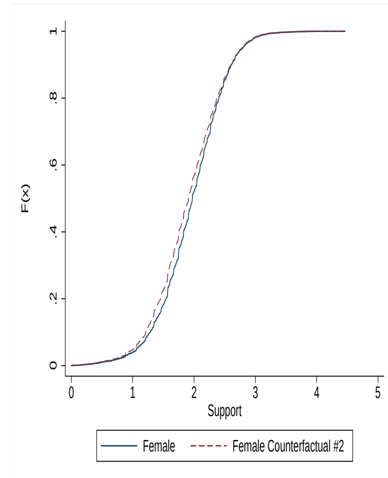
Figure 29: CDF Comparisons of Female and Female Counterfactual #2 Wage Distributions (1976-1984)



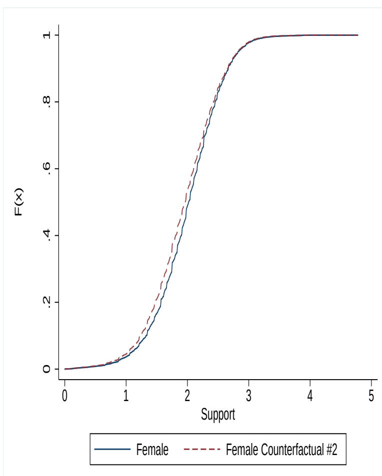
(a) 1985



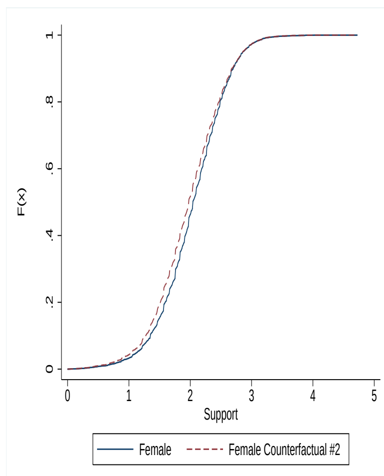
(b) 1986



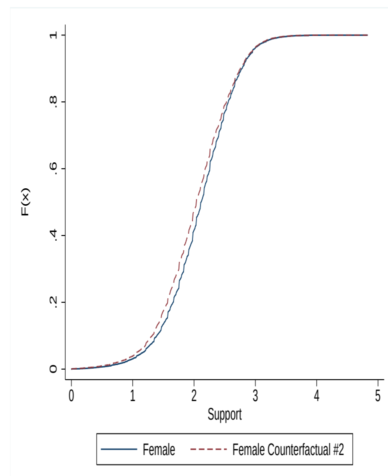
(c) 1987



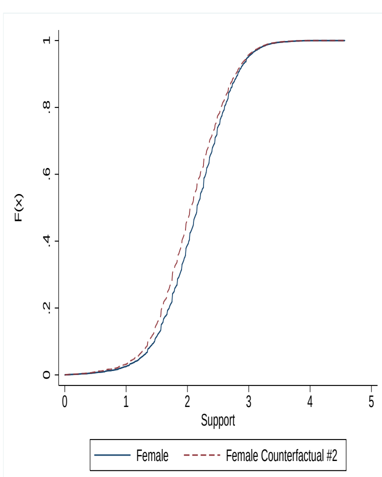
(d) 1988



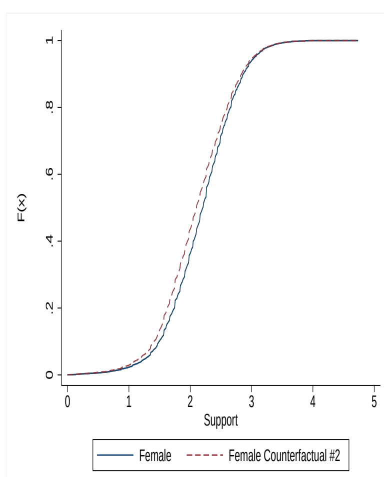
(e) 1989



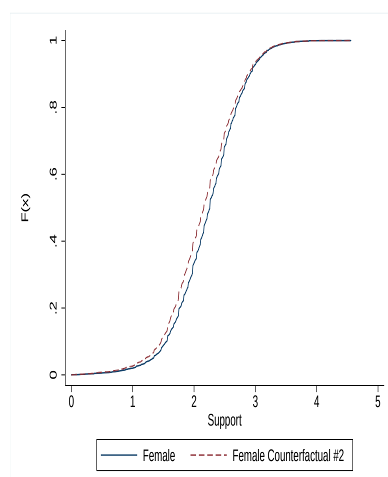
(f) 1990



(g) 1991

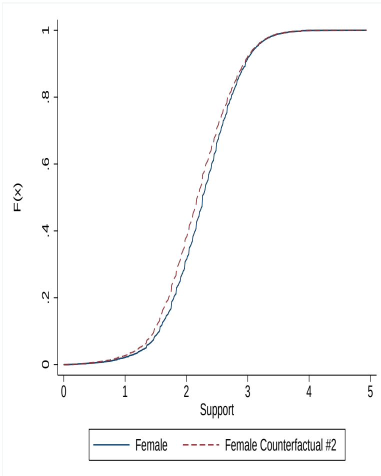


(h) 1992

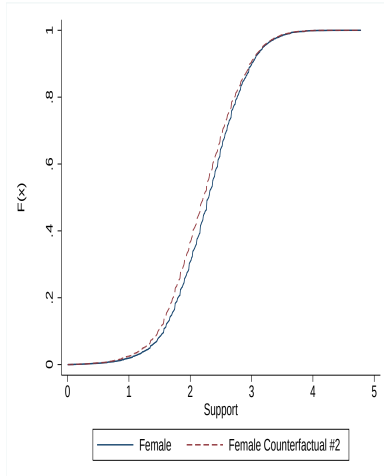


(i) 1993

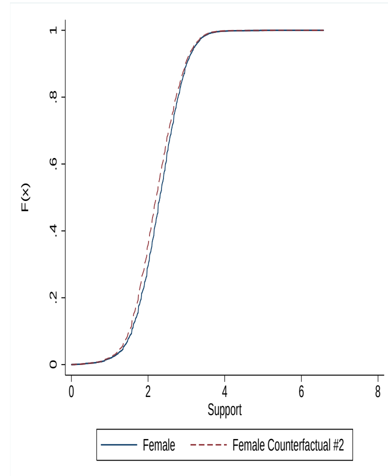
Figure 30: CDF Comparisons of Female and Female Counterfactual #2 Wage Distributions (1985 - 1993)



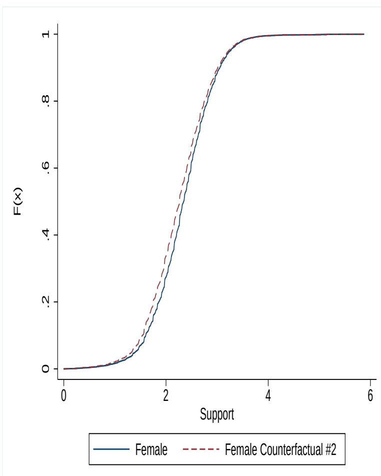
(a) 1994



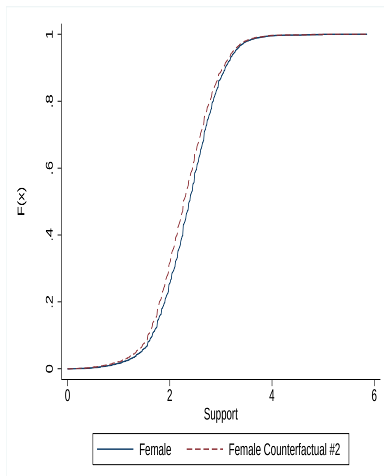
(b) 1995



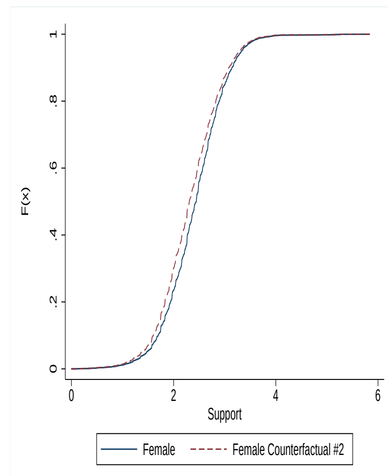
(c) 1996



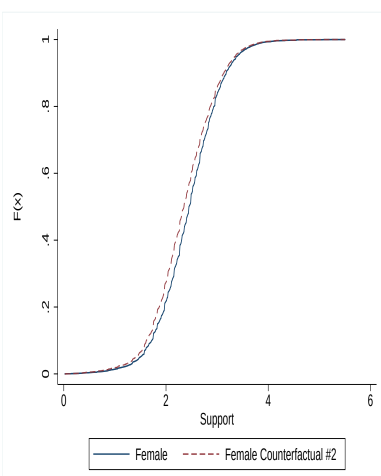
(d) 1997



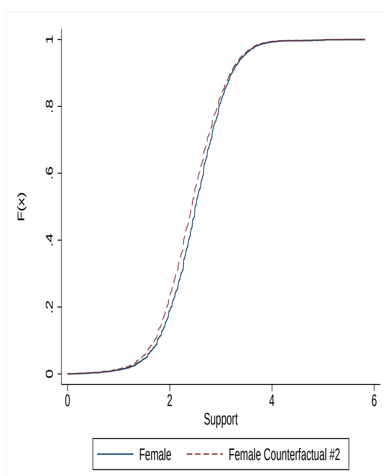
(e) 1998



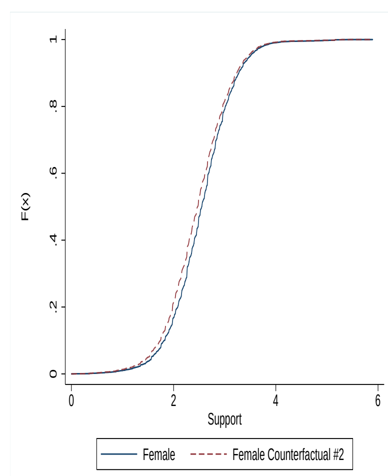
(f) 1999



(g) 2000

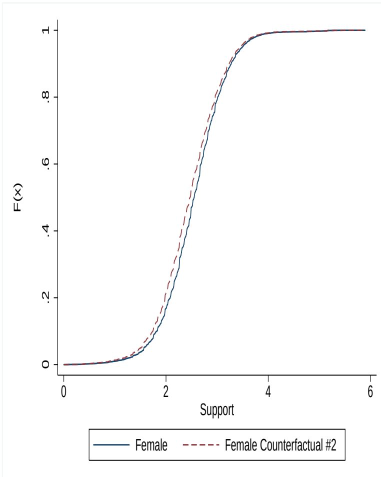


(h) 2001

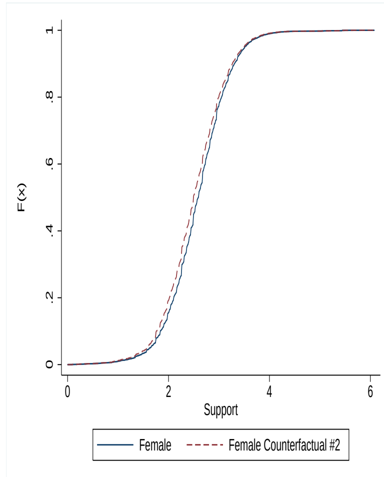


(i) 2002

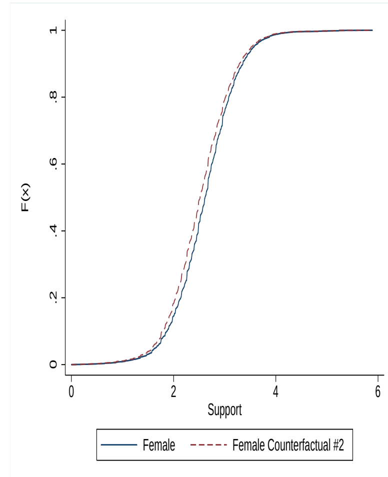
Figure 31: CDF Comparisons of Female and Female Counterfactual #2 Wage Distributions (1994 - 2002)



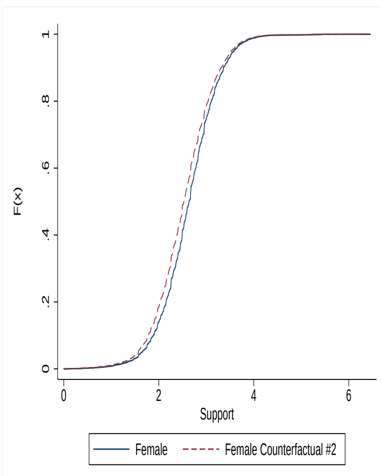
(a) 2002



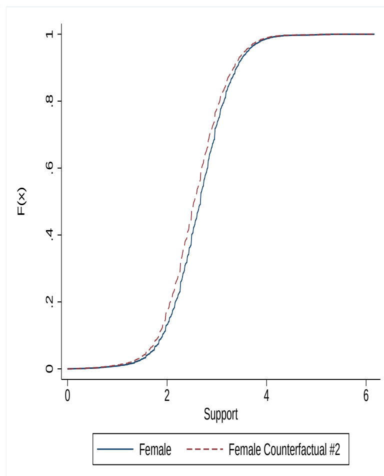
(b) 2003



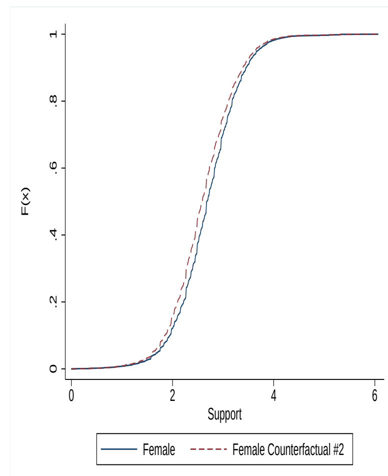
(c) 2004



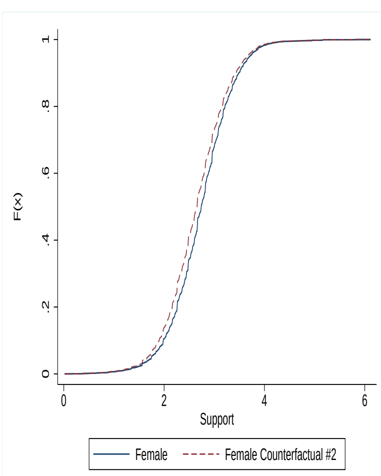
(d) 2005



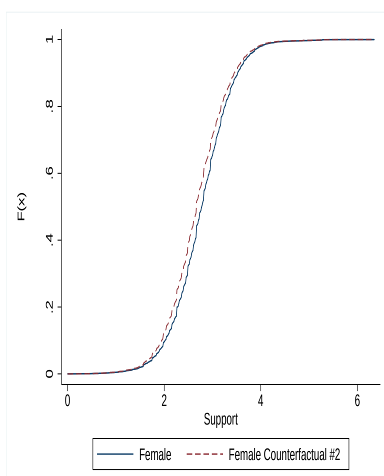
(e) 2006



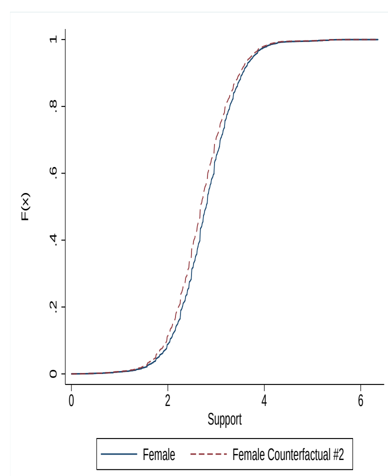
(f) 2007



(g) 2008

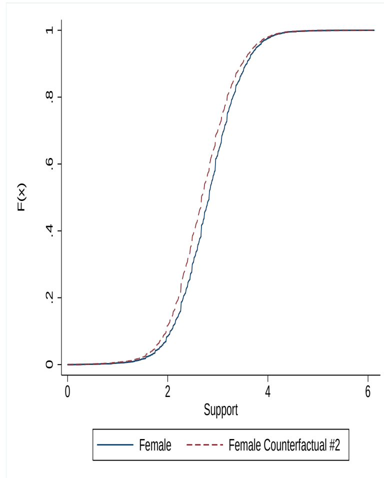


(h) 2009



(i) 2010

Figure 32: CDF Comparisons of Female and Female Counterfactual #2 Wage Distributions (2002 - 2010)



(a) 2011

Figure 33: CDF Comparisons of Female and Female Counterfactual #2 Wage Distributions (2011)

Table A1: The Patterns of Changes in Measures of The Gender Gap

Year	$S_\rho \times 100$ (1)	Mean (2)	10th (3)	25th (4)	50th (5)	75th (6)	90th (7)
1977	D	D	D	D	I	D	D
1978	D	I	I	I	D	I	D
1979	D	D	D	D	I	I	I
1980	D	D	D	D	D	D	D
1981	D	D	D	D	D	D	I
1982	D	I	I	I	I	I	D
1983	D	D	D	D	D	D	I
1984	D	D	D	D	D	D	D
1985	D	I	I	D	I	I	I
1986	D	D	I	I	D	D	D
1987	D	D	I	D	D	D	D
1988	D	D	D	D	D	D	D
1989	D	D	I	I	I	D	I
1990	D	D	D	D	D	D	D
1991	D	D	D	I	D	D	D
1992	D	D	D	D	D	D	I
1993	D	D	D	D	D	I	D
1994	D	D	I	D	I	D	D
1995	I	I	I	I	I	I	D
1996	D	I	I	I	D	D	-
1997	D	D	D	D	D	D	D
1998	I	I	D	I	I	D	I
1999	I	D	I	D	D	I	D
2000	D	D	I	D	I	I	D
2001	I	I	I	I	I	I	I
2002	D	D	D	I	D	D	D
2003	D	D	I	D	D	I	D
2004	D	D	D	D	D	D	D
2005	I	D	D	D	D	D	I
2006	D	I	I	I	D	D	D
2007	D	D	D	D	I	D	D
2008	D	D	I	D	D	D	D
2009	I	I	D	I	D	D	I
2010	D	D	I	I	I	I	D
2011	D	D	I	D	D	I	D

[1] Data Source: IPUMS CPS (`http://cps.ipums.org/cps/`). Column (1) reports the overal gender gap ($\times$100) at corresponding functionals of the distributions of log wages (measures the distance between the female and male wage distributions). Columns (2)- (6) report conventional measures based on difference in parts of the wage distributions between males and females. The cells with "I" highlighted in green are the years when the measure increased, while the cells with "D" highlighted in light grey are the years when the measure decreased.

Table A2: Significance Testing of S_ρ

Year	Female v.s. Male			Female v.s. Counterfactual #1			Female v.s. Counterfactual #2		
	90^{th}	95^{th}	99^{th}	90^{th}	95^{th}	99^{th}	90^{th}	95^{th}	99^{th}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1976	0.06	0.07	0.08	0.07	0.08	0.10	0.07	0.08	0.10
1977	0.04	0.05	0.05	0.06	0.06	0.07	0.05	0.06	0.06
1978	0.04	0.05	0.05	0.07	0.07	0.08	0.06	0.07	0.08
1979	0.05	0.05	0.06	0.06	0.06	0.07	0.05	0.05	0.07
1980	0.05	0.05	0.06	0.06	0.06	0.07	0.05	0.05	0.07
1981	0.04	0.04	0.04	0.05	0.05	0.06	0.04	0.04	0.05
1982	0.05	0.05	0.06	0.06	0.07	0.08	0.05	0.06	0.06
1983	0.04	0.05	0.05	0.05	0.06	0.07	0.05	0.05	0.06
1984	0.04	0.05	0.05	0.05	0.06	0.07	0.05	0.05	0.06
1985	0.04	0.05	0.05	0.05	0.05	0.06	0.04	0.05	0.06
1986	0.04	0.05	0.05	0.06	0.07	0.08	0.06	0.06	0.07
1987	0.04	0.05	0.06	0.06	0.06	0.07	0.05	0.05	0.06
1988	0.04	0.04	0.05	0.05	0.05	0.06	0.04	0.04	0.05
1989	0.04	0.05	0.05	0.05	0.06	0.07	0.05	0.05	0.06
1990	0.03	0.04	0.05	0.04	0.05	0.06	0.04	0.04	0.05
1991	0.03	0.04	0.04	0.04	0.04	0.05	0.04	0.04	0.05
1992	0.04	0.04	0.05	0.05	0.05	0.06	0.04	0.04	0.05
1993	0.04	0.04	0.05	0.04	0.05	0.06	0.04	0.04	0.05
1994	0.04	0.05	0.05	0.05	0.06	0.07	0.05	0.06	0.07
1995	0.04	0.05	0.05	0.05	0.05	0.05	0.04	0.05	0.05
1996	0.05	0.05	0.06	0.06	0.06	0.07	0.05	0.05	0.06
1997	0.06	0.06	0.07	0.06	0.06	0.07	0.05	0.06	0.07
1998	0.04	0.05	0.06	0.05	0.06	0.07	0.05	0.05	0.07
1999	0.04	0.05	0.06	0.05	0.05	0.06	0.05	0.05	0.06
2000	0.05	0.06	0.07	0.06	0.06	0.07	0.04	0.05	0.06
2001	0.04	0.04	0.04	0.04	0.05	0.05	0.03	0.04	0.04
2002	0.03	0.03	0.03	0.04	0.04	0.04	0.03	0.04	0.04
2003	0.03	0.04	0.04	0.04	0.04	0.05	0.03	0.04	0.04
2004	0.04	0.04	0.04	0.04	0.04	0.05	0.04	0.04	0.05
2005	0.04	0.04	0.04	0.04	0.05	0.05	0.04	0.04	0.05
2006	0.04	0.04	0.04	0.04	0.05	0.05	0.04	0.04	0.05
2007	0.04	0.04	0.04	0.04	0.05	0.05	0.04	0.04	0.05
2008	0.03	0.04	0.04	0.04	0.04	0.05	0.03	0.04	0.04
2009	0.04	0.04	0.05	0.05	0.05	0.06	0.04	0.04	0.05
2010	0.04	0.04	0.05	0.05	0.05	0.06	0.04	0.04	0.05
2011	0.04	0.04	0.04	0.04	0.05	0.05	0.03	0.04	0.04

[1] Data Source: IPUMS CPS (`http://cps.ipums.org/cps/`). Columns (1)-(3) report the 90th, 95th, and 99th percentiles obtained under the null of no difference between male and female wage distributions ($\times 100$). Columns (4)-(6) report the 90th, 95th, and 99th percentiles obtained under the null of no difference between female and the counterfactual wage #1 distributions (($\times 100$)); Columns (7)-(9) report the 90th, 95th, and 99th percentiles obtained under the null of no difference between female and counterfactual wage #2 distributions (($\times 100$)).