Technological Change and Gender Wage Differentials

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Abstract

This paper investigates the impact of non-neutral technological change on the recent narrowing of the gender wage differentials. The relation between technological change and relative wages of female and male workers is modeled through a constant elasticity of substitution production function that incorporates male and female labor inputs by occupation in each industry, a non-labor input and a productivity parameter function that captures non-neutral technological change. Data from 1979 to 2001 on employment and wages by industry and occupation come from the Current Population Survey. Using a non-linear

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two stage least square with cross-equation restrictions, the estimated results provide evidence that non-neutral technological change partially explains the documented narrowing of the gender wage gap during the 1980s and 1990s, even after controlling for unexplained differences in gender relative wages. Specifically, changes in non-neutral technological change explain between 1 % and 1.7 % of the 19.4% overall increase of women's wages relative to men's in the sample. The strongest effect is found at the highest pay occupation level, while the smallest effect at the lower pay occupations. Finally, this paper brings evidence that ignoring the unexplained component of the gender wage differentials could result in an upward biased estimation of the effect on non-neutral technological change on the gender wage gap.

JEL Classification: J31, O33

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INTRODUCTION

The effect of new technologies on wages and employment is a question that has always interested economists. This topic has received considerable attention as the wage inequality in the U.S. labor market has experienced a dramatic increase from the late 70's into the 90's, increase believed to be associated with new technologies adopted by firms during this period of time. As summarized by Katz and Autor (1999), the main changes that took place in the U.S. wage structure during the 1980's and 1990's are translated into large increases in wage differentials between blue-collar and white-collar workers and by much greater residual inequality, that is, larger within group wage dispersion. The wage dispersion increased substantially for both men and women – the weekly earnings of the 90^{th} percentile worker relative to the 10^{th} percentile worker increased by over 25% for both men and women from 1979 to 1995. The wage differentials by education, occupation and experience have increased as well – the relative earnings to college graduates and those with advanced degrees increased dramatically in the 1980s. At the same time, the employment shares of less skilled workers appear to have fallen relative to those of more skilled workers (Berman, Bound and Griliches, 1994). This recent rise in wage inequality has been primarily attributed in the literature to increased relative demand for highly educated and 'more skilled' workers, driven by skill-biased technological change, largely associated with the new information technology.[1]

[1] Bound and Johnson (1992), and Berman et al. (1994), attribute wage structure changes to an increased rate of growth of the relative demand for highly educated and 'more skilled' workers driven by skill-biased technological changes, largely associated with the spread of computers (information technologies) in the workplace. When the explanatory power of technological change proxies is considered (investment in computers, employee computer use, R&D, R&D intensity) the results are even more convincing, showing that technological change has significantly affected the changes in skill composition of the labor force and the wage dispersion. See Card, D., DiNardo, J. E.(2002)

The major exception from this pattern of a widening wage structure has been the substantial narrowing of wage differentials between men and women during the last couple of decades. The statistical data show that gender wage differentials declined both overall and for all ages and education groups in the 1980s and 1990s.

Historical trends on the gender wage gap show that there is essentially no significant change in the gender gap in the period immediately post-World War II, explained by the failure of women's skills to increase relative to men's (Goldin, 1990). During the 1960s and 1970s, the seemingly failure of the gender gap to narrow was troubling, since during this period of time a significant rise in women's labor force participation was documented. However, starting with the 1980's, the gender gap narrowed at a rapid pace through the early 1990s, and then slowed somewhat during the mid-1990s. The rapid convergence in the gender gap during this period surprised many observers, especially in the light of the earlier lack of convergence. Today, women's pay still lags men's in virtually every sector of the economy. Full-time female workers made 77.5 percent of what their male counterpart did in 2001, according to the Bureau of Labor Statistics.

There is a large literature in labor economics that attempts to explain the trends in gender wage differentials. However, this literature, largely independent of the literature on non-neutral, skill-biased technological change continues to leave open the question of the effect of new technologies on the gender wage gap. This paper attempts to contribute to the labor literature by investigating the recent narrowing of the gender wage gap in the context of technological change. Previous literature (Berman et. al., 1994) shows that, during the last couple of decades, technological change significantly raised the return to skill, including unobserved skills. But is the return to skill rising equally for men and women? This paper argues that technological change, associated primarily with new information technology might enable female workers in possibly

for a survey of the literature in this area.

different ways than men. One would think that new technologies would at least continue to take away from the emphasis on the physical strength of some jobs. However, this is not the only way technology might affect the relative wages of female and male workers. It might be possible that women have unobserved skills that are more compatible with computer use than men, generating a faster rise of the return to unobservables for women, relative to men, as a result of the impact of technological change. The literature on technological gender gap emphasizes the different approach of women to technology (i.e. use of computers), relative to men. This difference is observed starting with middle school, among boys and girls.[2] While men are more interested in the computer as a 'machine', a bundle of hardware and software, women, on average, are more interested in the functions of computers, approaching technology as a way to better handle tasks, as means of integrating information, increasing communication with clients, improving work and as well as inter-personal relations. One high profile example of such different approaches to computers is that of Bill Gates of Microsoft and Meg Whitman, the CEO of pioneering online auctioneer eBay Inc. As described by the BusinessWeek magazine, Meg Whitman masterminded eBay's continuing expansion making use of new technologies and combining them with great brand and consumer instincts.[3] This paper argues that the different approach to the use of new technologies might generate different returns to skill / computer use for women and men. Bresnahan (1997) introduces the idea of an organizational complementarity between computers and workers who posses both greater skills, but also greater 'people' skills, or 'soft' skills. If educated women are more likely to have these 'soft' skills than educated men, the return to computer use will be larger for women than men.

[2] C. Brunner, 1999, Merrow Report, Center for Children and Technology, part of the Bank Street College of Education in New York City, as cited by Becky Whittenburg "The Technology Gender Gap. How Are We Doing? ", Gray Matters Volume 3, Issue 3, May, 2000.

[3] Kerstetter, Jim. "Meg Whitman", BusinessWeek, May 15, 2000.

A few papers indirectly point to non-neutral technological change as a potential factor that might explain some of the gender wage narrowing trends. O'Neill and Polachek (1993) analyzed the trend of the gender wage gap in the 1980s, when the gender gap experienced the sharpest change, and found that convergence in measurable work-related characteristics (schooling and work experience) explains one-third to one-half of the narrowing. The remainder is attributed to declining wages of blue-collar workers heavier represented by men than women, declining considered by later work (Berman et al. 1994) to be driven by skill-biased technological change.

Blau and Kahn (2000) investigate the effect of gender-specific factors (including gender differences in qualifications, and discrimination) and the overall wage structure on the recent gender pay gap in the U.S. in a labor supply approach. Their test of the effect of technological change on the gender pay gap uses the overall wage structure changes as an explanation for the gender wage differences. They attribute the declining gender differentials primarily to gender-specific factors, specifically the convergence of work-related skills.

In the light of the recent changes in the wage structure, the narrowing of the gender wage gap during the last couple of decades has puzzled the economists. Previous results, cited by Blau and Kahn, 1994, suggest that, on average, women tend to be less skilled than men and to be located in lower-paying industries and occupations. This will imply that an increase in the return to experience would cause the gender wage gap to rise, even if women's relative level of experience and their gender-specific treatment by employers remained the same. Similarly, an increase in the return to better paid, 'male' occupations and industries would widen the gender wage gap. As formulated in Card and DiNardo (2002), the trends in the gender wage gap are believed to pose "problems and puzzles" for different versions of the non-neutral technological change hypothesis. The narrowing of the wage gap in the 1980s is considered a problem for the rising return-to-skill version of non-neutral technological change, which predicts that technological change raises the return to skill, including the unobserved skills that are usually hypothesized to explain the gender gap. If women use computers on the job more than men, the narrowing gap is consistent with the computer-use-skill-complementarity version of non-neutral technological change. But this cannot explain the similarity of the trends in the gender wage gap for different levels of education, since well-educated women are documented to actually be less likely to use computers than well-educated men.

A previous paper by Allen (2001) reports evidence on how technological change is related to changes in wage gaps by schooling, experience and gender. Using individual level data from the 1979 and 1989 Current Population Survey (CPS), combined with industry level data on technology for 39 industries, Allen finds that levels and changes in the return to schooling and experience are significantly related to R&D, tech capital and K/L acceleration. Concerning the gender wage differentials, Allen reports that the gender gap narrowed more in industries that most intensively used high-tech capital in 1979. He also reports that wage growth rises with schooling and experience and is greater for women than for men.

This paper attempts to shed some light on these issues by directly investigating the narrowing of the gender wage gap in the context of technological change. The investigation is conducted at a more disaggregated level, by occupation and industry, to capture any potential differences in the effect of new technologies on the relative wages of female and male workers, both in the manufacturing and non-manufacturing sectors, from 1979 to 2001. These years cover the period of time that witnessed the most significant narrowing trend of the gender wage gap. The relation between non-neutral technological change and the gender wage differentials is modeled through a constant elasticity of substitution (CES) production function that incorporates male and female labor inputs by occupation in each industry, a non-labor input and a productivity parameter function that captures non-neutral technological change. The relation between technological change and gender relative wages is identified by using a novel approach that allows to separately estimate the effects of technological change and discrimination on the gender wage gap. A gender based wage discrimination factor is introduced, along with the non-neutral technological change, to further explore the narrowing of the gender wage gap. If the unexplained differences of the gender wage gap (discrimination) are not considered, the estimated elasticity of factor substitution is biased downward.

The key results of this paper provide evidence that non-neutral technological change had an impact on the narrowing of the gender wage gap during the last two decades, with differences across industries and occupations. The robustness of the results is tested by using direct measures of technological change. The results obtained when direct measures of technological change are used are similar in sign and magnitude. Finally, this paper brings evidence that ignoring the unexplained component of the gender wage differentials could result in an upward biased estimation of the effect on non-neutral technological change on the gender wage gap.

The rest of the paper is organized as follows: section 2 presents the conceptual framework, section 3 is concerned with empirical issues, section 4 describes the data used in the analysis, section 5 presents the results and section 6 concludes. Tables with variables definition, descriptive statistics and results follow at the end of the paper.

CONCEPTUAL FRAMEWORK

A CES Production Function with Non-Neutral Technological Change

To illustrate the concept of non-neutral technological change in relation to gender wage differentials, assume that non-neutral technological change can be modeled as a shift in an industry-wide production technology that can be characterized by a constant elasticity of substitution (CES)[4] production function of the following form:

$$Q_t = A(t)\left[\sum_{j=1}^{J}\alpha_j(t)\,L_{jt}^{\rho} + \left(1-\sum_{j=1}^{J}\alpha_j(t)\right)K_t^{\rho}\right]^{\frac{\phi}{\rho}}, \tag{1}$$

where Q_t is a measure of output in quarter t, $A(t)$ is a scale parameter that captures the neutral technological change, L_{jt} represents employment in quarter t, the j^{th} category of labor (where categories are defined by gender and four occupations within each industry), J is the number of distinct labor inputs, defined by gender and occupation, within each industry, t stands for quarters, K_t is a measure of non labor inputs in quarter t, and $\alpha_j(t)$ is a productivity parameter function that captures technological change by measuring the savings in one factor input relative to the others. The specification of $\alpha_j(t)$ will be discussed below. Note that ϕ is the returns to scale parameter and $\rho = \frac{\sigma-1}{\sigma}$, where σ is the elasticity of substitution among inputs.

The marginal products can be derived as:

$$MP_{L_{jt}} = \phi A(t)\,\alpha_j(t)\,L_{jt}^{\rho-1}Q_{jt}^{\frac{1-\rho}{\rho}} \tag{2}$$

and

$$MP_{Kt} = \phi A(t)\left[1-\sum_{j=1}^{J}\alpha_j(t)\right]K_t^{\rho-1}Q_{jt}^{\frac{1-\rho}{\rho}}. \tag{3}$$

Assuming cost minimization, the marginal products will be equated with the factor input prices:

$$\frac{MP_{L_{jt}}}{MP_{L_{ht}}} = \frac{w_{jt}}{w_{ht}}, \quad j \neq h \tag{4}$$

and

$$\frac{MP_{Kt}}{MP_{Ljt}} = \frac{r_t}{w_{jt}}. \tag{5}$$

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[4] Using Cobb-Douglas or Leontief production technologies, as special cases of the CES production functio, would not yield identifiable biases because the elasticity of substitution in these cases is either unity or zero.

By substituting (2) and (3) into (4) and (5), and by normalizing relative to the h^{th} labor input (i.e. L_{ht}, and w_{ht}) one will obtain the following:

$$\frac{\alpha_j(t) L_{jt}^{\rho-1}}{\alpha_h(t) L_{ht}^{\rho-1}} = \frac{w_{jt}}{w_{ht}}, \ j \neq h \tag{6}$$

and

$$\frac{\left[1 - \sum_{j=1}^{J} \alpha_j(t)\right] K_t^{\rho-1}}{\alpha_h(t) L_{ht}^{\rho-1}} = \frac{r_t}{w_{ht}}. \tag{7}$$

Taking the log of the above relations the following set of equations result, of the form:

$$\ln\left(\frac{w_{jt}}{w_{ht}}\right) = \ln\left(\frac{\alpha_j(t)}{\alpha_h(t)}\right) + (\rho - 1)\ln\left(\frac{L_{jt}}{L_{ht}}\right), \ j \neq h \tag{8}$$

and

$$\ln\left(\frac{r_t}{w_{ht}}\right) = \ln\left(\frac{\left[1 - \sum_{j=1}^{J} \alpha_j(t)\right]}{\alpha_h(t)}\right) + (\rho - 1)\ln\left(\frac{K_t}{L_{ht}}\right). \tag{9}$$

The specification of the $\alpha_j(t)$ functions is as given by a multinomial logit form:

$$\alpha_j(t) = \frac{e^{\alpha_{j0} + \alpha_{j1}\left(\frac{1}{t}\right) + \epsilon_{jt}}}{1 + \sum_{j=1}^{J} e^{\alpha_{j0} + \alpha_{j1}\left(\frac{1}{t}\right)}}, \ j = 1, ..., J \tag{10}$$

and

$$\alpha_{J+1}(t) = 1 - \sum_{j=1}^{J} \alpha_j(t) = \frac{1}{1 + \sum_{j=1}^{J} e^{\alpha_{j0} + \alpha_{j1}\left(\frac{1}{t}\right)}}. \tag{11}$$

Let $0<\alpha_j<1$ and $\sum_{j=1}^{J+1} \alpha_j(t) = 1$, the last restriction being necessary for the identification of the $\alpha's$. ϵ_{jt} is a random error term, distributed N(0, σ).

Given the specification of the $\alpha_j(t)$ functions, the equations (8) and (9) become estimating equations of the following form:

$$\ln\left(\frac{w_{jt}}{w_{ht}}\right) = \beta_{j0} + \beta_{j1}\frac{1}{t} + (\rho - 1)\ln\left(\frac{L_{jt}}{L_{ht}}\right) + \epsilon_{jt}, \ j \neq h, \tag{12}$$

and

$$\ln\left(\frac{r_t}{w_{ht}}\right) = \beta_{h0} + \beta_{h1}\frac{1}{t} + (\rho - 1)\ln\left(\frac{K_t}{L_{ht}}\right) + \epsilon_{ht}, \tag{13}$$

where $\beta_{j0} = \alpha_{j0} - \alpha_{h0}$, $\beta_{j1} = \alpha_{j1} - \alpha_{h1}$ with $j \neq h$, and $j = 1, ..., J$ for equations (12), and $\beta_{h0} = -\alpha_{h0}$ for equation (13). In this specification, the effect of the non-neutral technological change is going to be captured by the coefficients of $\frac{1}{t}$. It is not necessary to sign the β_{j1} parameters that capture the technological change. With this specification the $\alpha_j(t)$ functions capture the savings in pairs of one labor or non-labor input relative to another, while the inverse of t insures a bounded measure of such savings. $(\rho - 1)$ will allow to estimate the elasticity of substitution between factors of production, since σ, the factor elasticity of substitution in each industry is equal to $\frac{1}{1-\rho}$.

A New Dimension: Gender Based Discrimination

The issue of gender based discrimination has been so extensively documented in the labor literature that it cannot be ignored as a potential major factor that shapes the gender wage gap. In this section a framework for incorporating the gender discrimination component is proposed. This framework allows to measure any potential gender based discrimination.

Following Gary Becker's (1971) decomposition of the relative wages of female and male workers into relative marginal product and a discrimination index, let the wage w_{ijt}^m of a male worker in quarter t , industry i, occupation j be given by its marginal product

$$w_{ijt}^m = MP_{L_{ijt}}^m \tag{14}$$

and the wage w_{ijt}^f of a female worker in quarter t , industry i, occupation j be given by its marginal product, discounted by a discrimination index d_t

$$w_{ijt}^f = \frac{MP_{L_{ijt}}^f}{(1 + d_t)}. \tag{15}$$

The wage equations for male workers in same industry, in occupation j, normalized to the wage of male workers in occupation h, where $j \neq h$,can be then written as:

$$\ln(\frac{w^m_{jt}}{w^m_{ht}}) = \alpha^m_{0,j-h} + \frac{\alpha^m_{1,j-h}}{t} + (\rho - 1)\ln(\frac{L^m_{jt}}{L^m_{ht}}) + \epsilon^m_{j-h,t}. \tag{16}$$

In this wage equation there is no gender based discrimination.

The wage equations for female workers in same industry, in occupation j, normalized to the wage of male workers in same industry, in occupation h will take into account potential gender based discrimination, and can be then written as:

$$\begin{aligned} \ln(\frac{w^f_{jt}}{w^m_{ht}}) &= \ln\left(\frac{MP^f_{jt}}{w^m_{ht}}\right) - \ln(1 + d_{j-h,t}) \\ &= \left(\alpha^{fm}_{0,j-h} - \alpha^m_{0,j-h} - d_{0,j-h}\right) + \left(\alpha^{fm}_{1,j-h} - \alpha^m_{1,j-h} - d_{1,j-h}\right)\frac{1}{t} \\ &\quad + [(\rho - 1) + d_{2,j-h}]\ln\left(\frac{L^f_{jt}}{L^m_{ht}}\right) + \epsilon^{fm}_{j-h,t} - \epsilon^m_{j-h,t} - u_{j-h,t}\ , \end{aligned} \tag{17}$$

where

$$\ln(\frac{MP^f_{jt}}{w^m_{jt}}) = \alpha^{fm}_{0,j-h} + \frac{\alpha^{fm}_{1,j-h}}{t} + (\rho - 1)\ln(\frac{L^f_{jt}}{L^m_{ht}}) + \epsilon^{fm}_{j-h,t} \tag{18}$$

and

$$\ln(1 + d_{j-h,t}) = d_{0,j-h} + \frac{d_{1,j-h}}{t} - d_{2,j-h}\ln(\frac{L^f_{jt}}{L^m_{ht}}) + u_{j-h,t}\ , \tag{19}$$

for j, h =1,... ,4 occupation index.

If one believes that there is potential gender based wage discrimination in the occupations considered, ignoring it could lead to estimating an ‘apparent’ elasticity of substitution σ between female and male labor inputs. This ’apparent’ estimated elasticity of substitution between female and male labor inputs without taking into account the potential discrimination is smaller than the actual elasticity of substitution, showing a diminished substitutability of female and male workers within the same occupation by potential gender based wage discrimination. To show this, note that $\frac{-1}{\sigma}+d_2 = -\frac{1}{\tilde{\sigma}}$. Since $d_2 < 0$, this implies that $\frac{1}{\sigma}<\frac{1}{\tilde{\sigma}}$. Thus, in the presence of discrimination, the estimated elasticity of factor substitution $\tilde{\sigma}$ is smaller than the true estimated σ, measuring the factor elasticity of substitution when there is no discrimination.

Non-Neutral Technological Change, Controlling for Skills and Potential Discrimination

Here we introduce a framework that allows us to estimate the effect of non-neutral technological change apart from the potentially confounding effects of changes in discrimination. By using data on individual characteristics (schooling, potential experience, potential experience squared), aggregated each quarter, by industry and occupation, a measure of discrimination can be derived.

Consider first the wage equation for a male worker k, in each industry, in occupation j, quarter t,

$$\ln w_{jtk}^{m} = X_{jtk}^{m}\hat{\beta}_{jt}^{m} + \upsilon_{jtk}^{m}. \tag{20}$$

Similarly, consider the wage equation for a female worker k, in each industry, in occupation j, quarter t,

$$\ln w_{jtk}^{f} = X_{jtk}^{f}\hat{\beta}_{jt}^{f} + \upsilon_{jtk}^{f}. \tag{21}$$

By using the estimated coefficients of the male and female workers' wages, a measure of unexplained differences can be obtained as:[5]

$$\ln(1 + D_{jt}) = \overline{X}_{jt}^{f}(\hat{\beta}_{jt}^{m} - \hat{\beta}_{jt}^{f}), \tag{22}$$

[5] Alternatively, the discrimination can be estimated by using the method proposed by Oaxaca & Ransom (1994). First, estimate a common wage structure for both male and female workers:

$lnw_{ijtk}^{m} = X_{ijtk}^{m}\tilde{\beta}_{ijt}^{m} + \upsilon_{ijt}^{m}$

Then, measure the discrimination as:

$ln\,(1 + D_{ijt}) = \overline{X}_{ijt}^{m}(\hat{\beta}_{ijt}^{m} - \tilde{\beta}_{ijt}) + \overline{X}_{ijt}^{f}(\tilde{\beta}_{ijt} - \hat{\beta}_{ijt}^{f})$

where $\overline{X}_{ijt}^{m}$ is the sample average, $\overline{X}_{ijt}^{m} = \sum_{k_m}(X_{ijtk}^{m}) * weight_{ijtk}^{m}$

and $\overline{X}_{ijt}^{f}$ is the sample average, $\overline{X}_{ijt}^{f} = \sum_{k_f}(X_{ijtk}^{f}) * weight_{ijtk}^{f}$. However, this alternative recquires a larger number of estimations, so it is more costly.

where $\overline{X}^f_{jt}$ is the sample average of workers' characteristics, $\overline{X}^f_{jt} = \sum_{k_f} (X^f_{jtk}) * weight^f_{jtk}$. The weights are provided by the BLS with the CPS data.

Following G. Becker (1971), the wage of a female worker relative to the wage of a male worker can be written as the difference between their relative marginal products and an index of discrimination:

$$\ln(\frac{w^f_{jt}}{w^m_{jt}}) = \ln\left(\frac{MP^f_{jt}}{MP^m_{jt}}\right) - \ln\left(1 + D_{jt}\right). \tag{23}$$

Thus, the relative marginal products can be written as:

$$\ln\left(\frac{MP^f_{jt}}{MP^m_{jt}}\right) = \ln(\frac{w^f_{jt}}{w^m_{jt}}) + \ln\left(1 + D_{jt}\right). \tag{24}$$

By replacing $ln\left(1 + D_{jt}\right)$ from equation (22), the following relation is obtained for the relative wages of male and female workers:

$$\ln(\frac{w^f_{jt}}{w^m_{jt}}) + \overline{X}^f_{jt}(\hat{\beta}^m_{jt} - \hat{\beta}^f_{jt}) = \alpha_{0,jt} + \alpha_{1,jt}\frac{1}{t} + (\rho - 1)\ln\left(\frac{L^f_{jt}}{L^m_{jt}}\right) + \epsilon_t. \tag{25}$$

Thus equation (24) above can be re-written in relative marginal products as:

$$\ln\left(\frac{MP^f_{jt}}{MP^m_{jt}}\right) = \alpha_{0,jt} + \alpha_{1,jt}\frac{1}{t} + (\rho - 1)\ln\left(\frac{L^f_{jt}}{L^m_{jt}}\right) + {\epsilon_t}^6. \tag{26}$$

Equation (26) above allows for the measurement of the impact of non-neutral technological change on the gender wage differentials, controlling for the unexplained wage gap (potential gender based discrimination).

[6] This last term comes from the Oaxaca decomposition, Oaxaca, (1973).

DATA DESCRIPTION

Data on Employment and Wages

In order to investigate the impact of non-neutral technological change on the gender wage gap, data from the Current Population Survey (CPS) on quarterly hourly wage and employment are used for female and male workers, for the years 1979 to 2001. The Data Appendix provides a description of the Current Population Survey. The data used here come from the NBER extracts of the CPS files. The extracts include micro data for approximately 30,000 individuals each month. About fifty variables each month are selected for continuity across years. For the purpose of this study quarterly employment and hourly wages data are used for full time employees, 16 years or over, aggregated quarterly by gender, industry and occupation. Table 1 lists the industry and occupation variables. There are eight major industries considered (Agriculture, Mining, Construction, Manufacture, Transportation, Trade, Finance and Services) and four major occupations (Executive and managerial occupations; Technical, sales and administrative support; Service occupations, mechanics and repairers; Machine Operators, laborers and farmers). Table 2 provides a description of the variables used in the estimations, while Table 3 provides summary statistics.

Chart 1 presents the trends of the relative employment and relative wages between men and women, from 1979 to 2001, based on the CPS data used in this paper. From the chart, one can clearly see the narrowing trend of the gender wage gap during this time interval. The overall ratio of women's wage to men's wages changed from 0.67 in the beginning of 1979 to 0.80 at the end of 2001. This represents a percentage change in the relative wages of 19.4% during this period of time. During the same time, the employment ratio of female to male workers went up from 0.57 to 0.70.

Data on Non-Labor Factor and Factor Price

Data on the non-labor input come primarily from the National Income and Product

Accounts (NIPA) tables of the Bureau of Economic Analysis. The series on K_t, the non-labor input, was obtained from recurrent equations, given initial conditions for K_t, and a certain rate of capital depreciation δ in each industry. To obtain series on r_t, the user cost of capital is used.

Here is how the data on the non-labor factor were obtained. Starting from the following accounting relation:

$$P_t Q_t = w_t L_t + r_t K_t \ , \tag{27}$$

data for $P_t Q_t$ were obtained from the NIPA Table 6.1, on National Income Without Capital Consumption Adjustment by Industry Group, while data on $w_t L_t$ came from BEA Table SQ7 (State Quarterly Income Estimates).

If capital consumption is defined as $C_t = \delta K_{t-1}$, δ can be calculated as:

$$\delta = \left(\frac{C_t}{K_{t-1}} \right) . \tag{28}$$

Data on $\delta r_{t-1} K_{t-1}$ can be retrieved from NIPA Tables 6.13 and 6.22, Non-corporate and Corporate Capital Consumption Allowances by Industry Group, while data on $r_{t-1} K_{t-1}$ can be retrieved from NIPA Table 3.3ES, Historical-Cost Net Stock of Private Fixed Assets by Industry, δ can be obtained.

Assuming zero profits, the user cost of capital can be calculated as follows:

$$r_t = (i_t + \delta) pd_t \ , \tag{29}$$

where i_t is the quarterly interest rate is from the Federal Reserve Historical Statistics, δ is the depreciation rate, calculated above, and pd_t is a price deflator, from NIPA table 7.6, Chain-Type Quantity and Price Indexes for Private Fixed Investment by Type. The K_t series can be recovered from (27):

$$K_t = \frac{(P_t Q_t - w_t L_t)}{r_t} . \tag{30}$$

By treating K_t this way, internal consistency of the data is insured. Summary statistics for the K_t and r_t series are listed in Table 3.

EMPIRICAL ISSUES

Estimation Strategy

Given the conceptual framework proposed in section 3, first subsection, the empirical investigation of the effect of the non-neutral technological change on the gender wage differences involves estimating a set of equations as described in (12) and (13).

The identification strategy for the coefficients will have to take into account some specific issues this model involves:

(a) cross-equation restrictions on ρ;

(b) endogeneity of the $\ln\left(\frac{L_{jt}^f}{L_{jt}^m}\right)$ variables, which requires proper instrumental variables.

The cross-equations restrictions on the ρ parameters results from the functional form of the production function, which implies an elasticity of substitution that does not vary with time, and it is the same for all pairs of labor, non-labor factors, for each industry. Thus, ρ will be restricted to have the same value across all equations, in each industry.

In what concerns the endogeneity of the $\ln\left(\frac{L_{jt}^f}{L_{jt}^m}\right)$ variables, in the standard elasticity of substitution equations, the dependent variable is the factor intensity in logs, $\ln\left(\frac{L_{jt}^f}{L_{jt}^m}\right)$, and the independent variable is $\ln\left(\frac{w_{jt}^f}{w_{jt}^m}\right)$. That is, $\ln\left(\frac{w_{jt}^f}{w_{jt}^m}\right)$ is considered exogenous since firms are assumed to be competitive in the factor market. However, at the industry level, the factor price ratios might be considered endogenous. Here, the focus is on the impact of technological change on gender wage differentials, thus, the factor price ratio is normalized as the dependent variable. Hence, the right hand side factor intensity variable is endogenous. In order to obtain consistent estimators it is necessary to consider estimation by instrumental variables. The instrumental variables used to solve the endogeneity problem are variables aggregated at the industry level that are believed to be correlated with the employment ratio, but uncorrelated with the error term.

The following instrumental variables are considered:

- the ratio of year-round, full time employed women to employed men (fwm);
- year-round, full time employed women to employed men in industry i (fwm_i);
- year-round, part time employed women to employed men (pwm);
- quarterly dummies (d_1, d_2, d_3);
- 3-month T-bill rates, quarterly averages[7], (i_t).

It is reasonable to consider that fwm, fwm_i and pwm are related with the ratio of full-time female-to-male workers in each industry, in occupation j, and unrelated with the error term. That is, it is reasonable to assume that changes in the gender composition of employment at the economy or industry level are correlated with the gender composition of the employment within an occupation, and uncorrelated with the specific wages of female and male workers within an occupation. A Hausman specification test with the null hypothesis that the IV estimator is consistent, and the OLS estimator is efficient and consistent, but inconsistent under the alternative hypothesis rejects the null hypotheses and validates the use of the instrumental variables in 84% of the equations. An overidentification test for the instrumental variables, with the joint null hypothesis that the excluded instruments are valid instruments, i.e., uncorrelated with the error term and correctly excluded from the estimated equation, does not reject the null, supporting the validity of the instruments. The first stage results are not reported in the results tables. The F-statistic for the excluded instruments passes the significance test for 86.11% of the equations.

[7] From the Federal Reserve Historical Statistics.

The equations (12) and (13) are estimated by Non-Linear Two Stage Least Squares (NL2SLS), the non-linearity being in coefficients. This is necessary for incorporating the cross-equations restriction mentioned above, plus the additional constraints that are coming from the internal logic of the model. To understand the need for such additional constraints, it is useful to look at the normalization and identification issues that come with the estimation of these demand equations, as described in the subsection below.

Normalization and Additional Constraints

The normalization used to derive equations (12) and (13) is relative to the labor input h, but the model can be specified as relative to any of the factor inputs. Staying with the normalization on the h^{th} labor input, it is straightforward to back out the effects on any set of wage differentials from the estimated model.

For example, if the h^{th} labor input corresponds to men workers in occupation 4, and the estimating equations (12) and (13) are written relative to the h^{th} labor input corresponds to men workers in occupation 4, if one is interested in the female/ male wage differentials for occupation 1, this can be recovered as:

$$\ln\left(\frac{w_{1t}^{f}}{w_{1t}^{m}}\right)=\left(\widehat{\beta}_{0,1-4}^{fm}-\widehat{\beta}_{0,1-4}^{m}\right)+\frac{\left(\widehat{\beta}_{1,1-4}^{fm}-\widehat{\beta}_{1,1-4}^{m}\right)}{t}+(\widetilde{\rho}-1)\ln\left(\frac{L_{1t}^{f}}{L_{1t}^{m}}\right)+\widehat{\epsilon}_{1t}^{fm}-\widehat{\epsilon}_{1t}^{m}\ , \tag{31}$$

where the coefficients $\widehat{\beta}_{1-4,v}^{fm}, \widehat{\beta}_{1-1,v}^{m}$, with $v = 0,\, 1$, are from the following two equations of the type (12):

$$\ln\left(\frac{w_{1t}^{f}}{w_{4t}^{m}}\right)=\widehat{\beta}_{0,1-4}^{fm}+\frac{\widehat{\beta}_{1,1-4}^{fm}}{t}+(\widetilde{\rho}-1)\ln\left(\frac{L_{1t}^{f}}{L_{4t}^{m}}\right)+\widehat{\epsilon}_{1-4,t}^{fm}\ , \tag{32}$$

and

$$\ln\left(\frac{w_{1t}^{m}}{w_{4t}^{m}}\right)=\widehat{\beta}_{0,1-4}^{m}+\frac{\widehat{\beta}_{1,1-4}^{m}}{t}+(\widetilde{\rho}-1)\ln\left(\frac{L_{1t}^{m}}{L_{4t}^{m}}\right)+\widehat{\epsilon}_{1-4,t}^{m}. \tag{33}$$

With these demand equations model, one needs $n-1$ equations to be able to span the entire system of equations, where n is the number of factor inputs. If non-neutral technological change narrows down the gender wage gap among skilled workers, we would expect $\widehat{\beta}^{fm}_{1,1-4} - \widehat{\beta}^{m}_{1,1-4} < 0$. One problem is that the estimated parameters would not be invariant with respect to the normalization; in other words, if the wage differentials were estimated relative to say wages of skilled females, one would have different estimates.

The skilled female/skilled male wage differential (female employed in occupation 1, Executive and managerial occupations) can also be directly estimated by:

$$\ln\left(\frac{w^f_{1t}}{w^m_{1t}}\right) = \widehat{\delta}^{fm}_{0,1-1} + \widehat{\delta}^{fm}_{1,1-1}\frac{1}{t} + (\widehat{\rho}-1)\ln\left(\frac{L^f_{1t}}{L^m_{1t}}\right) + \widehat{\nu}^{fm}_{1t} \ . \tag{34}$$

However, in general $\widehat{\delta}^{fm}_{0,1-1} \neq \left(\widehat{\beta}^{fm}_{0,1-4} - \widehat{\beta}^{m}_{0,1-4}\right)$, $\widehat{\delta}^{fm}_{1,1-1} \neq \left(\widehat{\beta}^{fm}_{1,1-4} - \widehat{\beta}^{m}_{1,1-4}\right)$, $\widetilde{\rho} \neq \widehat{\rho}$, $\widehat{\nu}^{fm}_{1t} \neq \widehat{\epsilon}^{fm}_{1t} - \widehat{\epsilon}^{m}_{1t}$.

This necessitates estimating $\binom{9}{2} = 36$ equations for all possible wage differential pairings with cross-equation restrictions in order to uniquely identify the estimated parameters. However, the residual variance/covariance matrix will be singular because the error terms will be perfect linear combinations of one another. Thus, a seemingly unrelated estimation (SURE) cannot be performed for all 36 equations simultaneously. This problem can be avoided by using a Non-Linear Two Stage Least Squares (NL2SLS) estimation method. The NL2SLS is used for all 36 possible pairings. However, because any 8 equations can span the rest of the 28 equations, for internal consistency additional constraints on the coefficients on the constant term and the inverse of time are imposed, for the remaining 28 equations to insure invariance of the estimating coefficients.

Since the focus on this paper is on the effect of non-neutral technological change on the gender wage differentials, only the estimation results pertinent to the relative gender wages in each one of the occupation considered are reported and discussed. The other results are available upon request from the authors.

Direct Measures of Technological Change

To directly test the power of specific factors in explaining the trends in the gender wage differentials in the recent past, proxies of technological chnage are considered. The measurement of technology is a problem inherent in all empirical work. This has been subject to investigation and controversy for many years. Among the several measures for technological change, R&D is the most popular. Other measures have been constructed and used, such as investment in computers, employee computer use, R&D intensity, capital intensity, K/L growth, total factor productivity (Berman et al. 1994, Allen, 2001, Card, D., DiNardo, J. E. 2002).

This paper employs as measures of technological change R&D investment, number of patents granted each year and R&D employment. These measures are chosen because of availability of consistent data for the years the investigation spans. The summary statistics of these measures are listed in Table 3. Only the results using R&D are reported.

RESULTS

The first set of results, reported in *Table 4,* show the estimated values of the impact of the non-neutral technical change on the gender wage differentials, without considering the possibility of discrimination. These estimates are obtained by using a Non-Linear Two Stage Least Squares (NL2SLS) estimation technique.

Before discussing these results, note that if non-neutral technological change had an effect on relative wages, this will translate into a statistically significant coefficient on $\frac{1}{t}$. Also, because of the link to the elasticity of factor substitution, the coefficient of $\frac{L^f_{jt}}{L^m_{jt}}$, $(\rho - 1)$, is expected to be negative and significant. Although estimated coefficients are obtained for all possible pairings of relative factor price ratios, only the results pertinent to the gender relative wages for each occupation are presented here, for each of the industries considered. This is motivated by the focus of this paper on the effect of non-neutral technological change on the relative wages of female and male workers within four distinct occupations. The other results are available upon request from the authors.

The results shown in Table 4 provide evidence of the effect non-neutral technological change on the narrowing of the gender based wage differentials for all four occupations in all industries. The strongest impact, in terms of the magnitude, is found at the level of managerial, scientific and professional specialty occupations, occupation 1, where all the coefficients on $\frac{1}{t}$ are negative and statistically significant across all industries. This implies that new technologies adopted by firms had contributed to the narrowing of the gender wage gap in the managerial and professional occupations, in all industries in the sample. At this occupation level, at the mean, changes in the non-neutral technology adopted by firms are raising the quarterly female-to-male wage ratio at an annualized rate that varies between .09% and .05%. The negative and strongly significant coefficients on $\frac{1}{t}$ suggest that, after controlling for skill, the non-neutral technological change is associated with a faster increase in the return to unobservables for women, relative to men, contributing to the narrowing of the gender gap.

The least impact was found at the lowest pay occupation levels, operators and laborers, occupation 4, where changes in non-neutral technology adopted by firms are raising the quarterly female-to-male wage ratio at an annualized rate that varies between .05% and .008%. For occupation 2, Technical, Sales and Administrative occupations, the effect of non-neutral technological change is mixed across industries. The estimates show no significant effect on the gender relative wages in agriculture, mining and finance. However, new technologies are associated with a decreasing gender wage gap in manufacturing and construction, while in transportation and retail the difference between wages of women and men workers became larger.

The estimated values for the elasticity of substitution between the factor inputs, σ, suggest that the labor inputs involved are substitutes in these industries-occupation cells.

Table 5 presents the estimated coefficients of the effect of non-neutral technological change, controlling for skills and discrimination, using the identification strategy presented in section 2. The sign and significance of the coefficients on $\frac{1}{t}$ remain largely the same as in Table 5. However, the magnitude of these coefficients is different. This suggests that, controlling for skills and potential employer discrimination, the portion of the narrowing gender gap explained by the effect of non-neutral technological change becomes smaller or larger, function of the sign of the unexplained gender wage differences taken into account. All coefficients on $\frac{1}{t}$ for occupation 1 are keeping the same sign and significance, however, the magnitude of the coefficients is smaller for all industries. This suggests that part of the narrowing of the gender wage gap is in fact explained by changes in employers' attitude toward gender discrimination. As discussed in section 2, not taking into account the unexplained wage differences will lead to an 'apparent' estimated σ, which is downward biased. By comparing the values of σ reported in Table 4 and Table 5, the values of σ are largely the same, with the exception of manufacturing, where controlling for unexplained wage differences (discrimination) generates a higher value for the factor elasticity of substitution. For agriculture and construction however, the values of σ are larger when controlling for discrimination. This might be explained for agriculture by the positive coefficients on $\frac{1}{t}$ for occupations 1 and 2, and no significance of this coefficient for occupation 3, as reported in Table 5, suggesting that in fact technological change has contributed to an increase of the wage gap. With this in mind, looking at the same coefficients for agriculture, but in Table 4, it may be inferred that in fact the discrimination had a narrowing effect on the gender wage gap (decreasing discrimination). This may explain why the value of the factor elasticity of substitution in Table 5 is smaller than the one reported in Table 4. For constructions, one can see that the sign, significance and magnitude of the coefficients on $\frac{1}{t}$ in Tables 4 and 5 are almost not changed.

When the direct measures of technological change are used, such as Total R&D expenditure in industry (from NSF Tables), the results, as reported in *Table 6* are similar with those reported for regressions using $\frac{1}{t}$, with a few exceptions. The impact of R&D investment in industry shows the highest effect on the relative wages of workers in managerial and professional occupations, occupation 1. The smallest effect on the gender wage ratio is found for occupations 2 and 4, Technical, Sales and Administrative Support, and Operators, Laborers respectively. For occupation 2, the sign of the inverse of RD is positive for Transportation, Finance and Services. Specifically, changes in the R&D expenditure by firms are raising the quarterly female-to-male wage ratio in occupation 1 at an annualized rate that varies between .035% and .008%. The smaller rate growth of women's wages attributed to R&D expenditure, relative to the growth rate due the non-neutral technological change may be explained by the fact that R&D expenditure is only one of the multi-dimensions of technological change. In terms of elasticities, the effects of $\frac{1}{t}$ and $\frac{1}{RD}$ are very similar. For occupation 1, the elasticity of the gender relative wages with respect to non-neutral technological change ranges between 0.011 and 0.006, while the elasticity with respect to R&D is between 0.011 and 0.002. The values of these elasticities seem small, but they reflect responses of the relative wage to quarterly changes in non-neutral technological change, and R&D respectively.

When the effect of the R&D expenditure is estimated, controlling for skills and unobserved differentials, the value of the coefficients on R&D are smaller. These results are reported in *Table 7.* The reduced magnitude of the coefficient is consistent again with the story that the 'apparent' effect of R&D on relative wages in fact was combined with the effect of changes in the discrimination behavior of employers.

The last set of results (nor presented) considers the possibility of gender wage discrimination and provides estimates for potential discrimination. However, this approach has shortcomings in that the effect of non-neutral technological change cannot be identified. These results provide an estimate of the unexplained portion of the gender relative wages (discrimination). Moreover, the signs and the magnitude of these coefficients confirm the story presented with the results from Tables 4 to 6. These results show that the discrimination coefficients are negative and significant for most of the occupations, indicating the presence of gender discrimination. Interestingly, the exception is in finance and services, where at the highest pay occupation, that is managerial and professional specialty occupations, there is evidence of gender favoritism toward women. Services are traditionally employing a larger percent of women, and this preference for women might explain these results.

CONCLUSIONS

This paper provides evidence of the impact of non-neutral technological change on the gender wage gap during the last two decades. The results suggest that changes in non-neutral technologies acquired by firms partially explain the documented narrowing of the gender wage differentials even after controlling for unexplained differences in gender relative wages (discrimination). Specifically, changes in non-neutral technological change explain between 1 % and 1.7 % of the 19.4% overall increase of women's wages relative to men's in the sample.

To obtain these estimated effects, the relation between non-neutral technological change and wages was modeled through a constant elasticity of substitution production function that incorporates male and female labor inputs by occupation in each industry, a non-labor input and a productivity parameter function that captures non-neutral technological change. The estimation employs quarterly CPS data on employment and wages, by industry and occupation, from 1979 to 2001. The model was estimated with a Non-Linear Two Stage Least Squares estimation method, with cross-equation restrictions.

The results suggest that changes in non-neutral technology contributed to the changes in the gender wage differentials differently across occupations. Specifically, non-neutral technological change contributed the most to changes in the gender wage gap at the level of managerial and professional occupations. These results are robust across all industries and specifications (controlling for unexplained differences in gender relative wages or using R&D, as a direct measure of technological change). For these managerial and professional occupations, at the mean, changes in non-neutral technologies adopted by firms are raising the quarterly female-to-male wage ratio at an annualized rate that varies between .09% and .05%.

The least impact was found at the lower pay occupations (operators and laborers), where, at the mean, the quarterly the female-to male wage ratio is raising at an annualized rate that varies between .05% and .008%. Again, these results are robust across industries and specifications.

The non-neutral technological change influenced the relative wages in favor of women in occupations 1 and 3, managerial and professional occupations, and service occupations, precision, craft and repair. However, in occupation 2, technical, sales and administrative occupations, the effect of the non-neutral technological change on relative wages contributed to a wider gender wage gap in some industries. This is an interesting result, since the documented narrowing trend of the gender wage ratio is very similar for different age and education groups. This suggests that different factors contributed in different proportions and directions to the narrowing trend of the gender wage ratio. It also suggests that the investigation of the narrowing trend of the gender wage gap would gain additional insight from an investigation at a more disaggregated level.

The results of this paper, providing estimates of the effect of non-neutral technological change on the gender wage gap by industry and occupation, bring additional insight to the question of the impact of technology on the gender wage gap. The significance, sign and magnitude of these estimates could guide further research to point to specific versions of non-neutral technological change, which might solve some of the 'problems and puzzles' summarized by Card and DiNardo (2002).

In the area of technology effect on the gender wage differences, a more flexible modeling approach that would relax the assumption of a constant elasticity of substitution across all factors could allow for a finer estimation of the impact of technology on the narrowing of the gender gap. This is left for future research.

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Table 1: Definition of Industry and Occupation Variables

I. **Industry Categories**

I1 Agriculture, Forestry and Fisheries

I2 Mining

I3 Construction

I4 Manufacturing

I5 Transportation, Communications & Utilities

I6 Wholesale and Retail Trade

I7 Finance, Insurance and Real Estate

I8 Services

II. **Occupational Categories**

Oc1 Managerial and Professional Specialty

Oc2 Technical, Sales and Administrative Support

Oc3 Service Occupations and Precision Production, Craft and Repair

Oc4 Operators, Fabricators and Laborers, Farming, Forestry and Fishing

Table 2: Description of Variables

Variable	**Description**
w^f_{ijt}	Hourly wage of full time female worker in industry i, occupation j, quarter t
w^m_{ijt}	Hourly wage of full time male worker in industry i, occupation j, quarter t
L^f_{ijt}	Employment of full time female worker in industry i, occupation j, quarter t
L^m_{ijt}	Employment of full time male worker in industry i, occupation j, quarter t
PTL^f_{it}	Employment of part time female worker in industry i, quarter t
PTL^m_{it}	Employment of part time male worker in industry i, quarter t
FTL^f_{it}	Employment of full time female worker in industry i, quarter t
FTL^m_{it}	Employment of full time male worker in industry i, quarter t
r_{it}	Non-labor Input factor price, in industry i, quarter t
K_{it}	Non-labor Input, in industry i, quarter t
i_t	3-months T-bill
QS_{it}	Share of Industry i Output in the Total Economy Output, in quarter t
RD_{it}	Total R&D expenditure for industry i, quarter t [millions]
P_t	Total count of granted patents in quarter t
RDE_{it}	Total R&D Employment for industry i, quarter t

Table 3: Summary Statistics

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**No. of Obs.**
L_t^f	1.28e+07	1113089	1.37e+07	1.77e+07	92
L_t^m	1.57e+07	71215.6	345375.2	661084.7	92
PTL_t^f	1886043	702460.3	30874.8	3968063	92
PTL_t^m	2246369	634580.8	1391054	1.53e+07	92
FTL_t^f	1.09e+07	1060273	8817634	1.26e+07	92
FTL_t^m	1.35e+07	758889.1	1.18e+07	1.48e+07	92
i_t	6.78263	2.914583	1.906	15.053	92
RD_t [thousands]	33426.02	8417.57	18695.35	50227.8	92

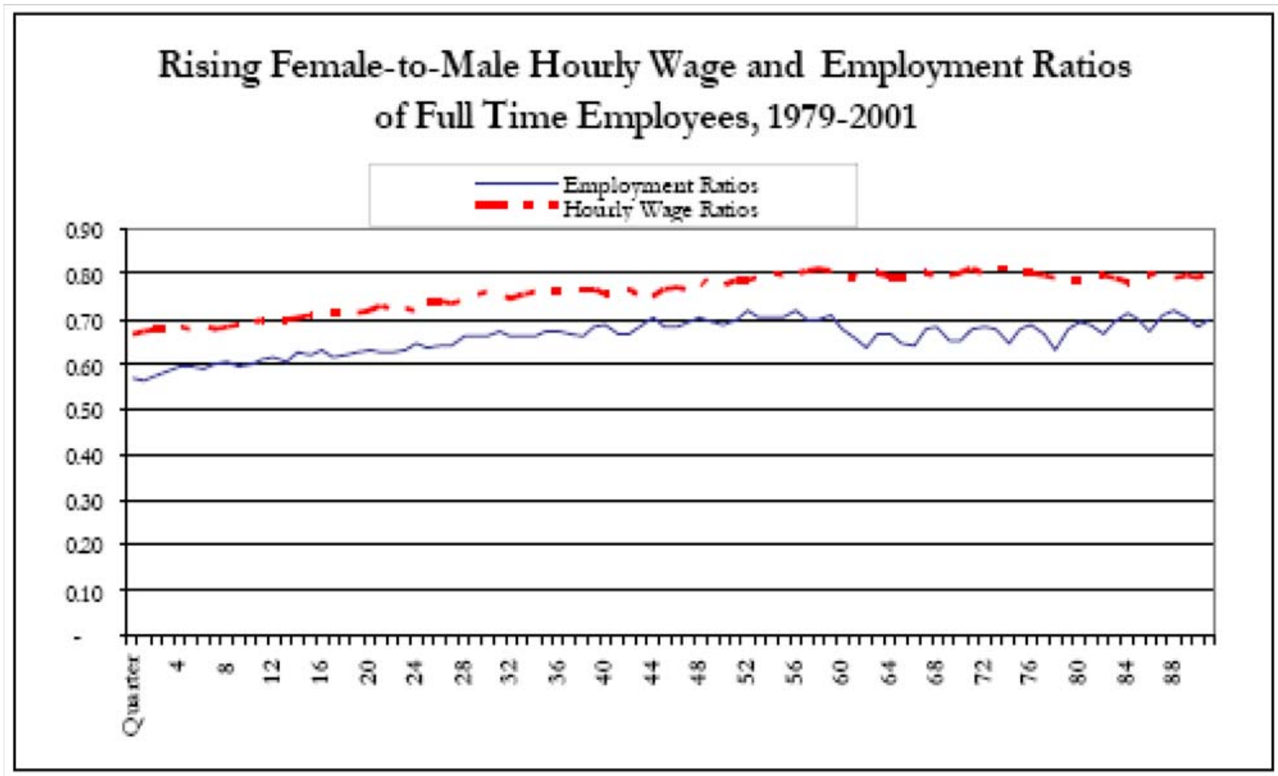

FIG. 1.

Source: The CPS data, 1979-2001

Table 4: NL2SLS with cross-equation restrictions for the estimation of the impact of non-neutral technological change

Industry 1 - Agriculture, Forestry and Fisheries

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	-.131*	(.016)	-.027*	(.012)	-.351*	(.025)	-.188*	(.017)
$\frac{1}{t}$	-.404*	(.073)	-.064*	(.045)	.168*	(.074)	-.049*	(.024)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.175*	(.021)	-.175*	(.021)	-.175*	(.021)	-.175*	(.021)
$\sigma_1 = \frac{1}{(1-\rho)}$	5.71							
No. Obs. 87								

Industry 2 – Mining

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.169*	(.019)	-.125*	(.006)	-.209*	(.031)	-.194	(.023)
$\frac{1}{t}$	-.408*	(.199)	-.003	(.069)	-.322*	(.125)	.121	(.104)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.098*	(.016)	-.098*	(.016)	-.098*	(.016)	-.098*	(.016)
$\sigma_2 = \frac{1}{(1-\rho)}$	10.20							
No. Obs. 72								

Industry 3 - Construction

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.038*	(.017)	-.106*	(.004)	-.423*	(.026)	-.372*	(.023)
$\frac{1}{t}$	-.390*	(.091)	-.133*	(.021)	-.285*	(.033)	-.081*	(.033)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.188*	(.014)	-.188*	(.014)	-.188*	(.014)	-.188*	(.014)
$\sigma_3 = \frac{1}{(1-\rho)}$	5.31							
No. Obs. 92								

Industry 4 - Manufacturing

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.050*	(.013)	-.136*	(.001)	-.403*	(.008)	-.235*	(.003)
$\frac{1}{t}$	-.413*	(.091)	-.028*	(.010)	-.245*	(.015)	.003	(.007)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.337*	(.010)	-.337*	(.010)	-.337*	(.010)	-.337*	(.010)
$\sigma_4=\frac{1}{(1-\rho)}$	2.96							
No. of Obs. 92								

Note: * Significant at a 95% level or better. Standard Errors in parantheses.

Industry 5 - Transportation, Communications & Utilities

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.069*	(.013)	-.093*	(.002)	-.460*	(.013)	-.578*	(.016)
$\frac{1}{t}$	-.367*	(.088)	.031*	(.016)	-.321*	(.028)	-.163*	(.024)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.417*	(.013)	-.417*	(.013)	-.417*	(.013)	-.417*	(.013)
$\sigma_5=\frac{1}{(1-\rho)}$	2.39							
No. Obs. 92								

Industry 6 - Wholesale and Retail Trade

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.131*	(.011)	-.189*	(.002)	-.266*	(.005)	-.309*	(.010)
$\frac{1}{t}$	-.389*	(.082)	.048*	(.015)	-.122*	(.017)	-.086*	(.014)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.307*	(.014)	-.307*	(.014)	-.307*	(.014)	-.307*	(.014)
$\sigma_6=\frac{1}{(1-\rho)}$	3.25							
No. Obs. 92								

Industry 7 - Finance, Insurance and Real Estate

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.182*	(.013)	-.054*	(.004)	-.537*	(.009)	-.545*	(.014)
$\frac{1}{t}$	-.507*	(.098)	.018	(.020)	-.030	(.036)	-.275*	(.073)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.557*	(.011)	-.557*	(.011)	-.557*	(.011)	-.557*	(.011)
$\sigma_7=\frac{1}{(1-\rho)}$	1.79							
No. Obs. 88								

Industry 8 - Services

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.249*	(.011)	.201*	(.004)	-.112*	(.001)	-.358*	(.004)
$\frac{1}{t}$	-.280*	(.083)	.083*	(.015)	.013	(.011)	-.018	(.018)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.600*	(.007)	-.600*	(.007)	-.600*	(.007)	-.600*	(.007)
$\sigma_8 = \frac{1}{(1-\rho)}$	1.66							
No. Obs. 92								

Note: * Significant at a 95% level or better. Standard Errors in parantheses.

Table 5: NL2SLS with cross-equation restrictions for the estimation of the impact of non-neutral technological change, taking into account the unexplained gender wage gap (discrimination)

Industry 1 - Agriculture, Forestry and Fisheries

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	-.242*	(.011)	-.021*	(.012)	-.391*	(.024)	-.226*	(.016)
$\frac{1}{t}$	-.176*	(.048)	.110*	(.048)	.166*	(.079)	-.047	(.032)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.246*	(.019)	-.246*	(.019)	-.246*	(.019)	-.246*	(.019)
$\sigma_1=\frac{1}{(1-\rho)}$	4.06							
No. Obs. 87								

Industry 2 – Mining

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	-.186*	(.012)	-.100*	(.012)	-.182*	(.030)	-.175*	(.027)
$\frac{1}{t}$	-.138*	(.079)	-.038	(.078)	-.212*	(.113)	.076	(.097)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.091*	(.015)	-.091*	(.015)	-.091*	(.015)	-.091*	(.015)
$\sigma_2=\frac{1}{(1-\rho)}$	10.98							
No. Obs. 72								

Industry 3 - Construction

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	-.296*	(.010)	-.068*	(.004)	-.443*	(.022)	-.391*	(.019)
$\frac{1}{t}$	-.308*	(.030)	-.113*	(.024)	-.234*	(.031)	-.087*	(.030)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.211*	(.011)	-.211*	(.011)	-.211*	(.011)	-.211*	(.011)
$\sigma_3=\frac{1}{(1-\rho)}$	4.71							
No. Obs. 92								

Industry 4 - Manufacturing

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	-.180*	(.005)	-.060*	(.003)	-.206*	(.006)	-.089*	(.005)
$\frac{1}{t}$	-.315*	(.014)	-.226*	(.011)	-.418*	(.013)	-.331*	(.013)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.242*	(.009)	-.242*	(.009)	-.242*	(.009)	-.242*	(.009)
$\sigma_4 = \frac{1}{(1-\rho)}$	4.13							
No. of Obs. 92								

Note: * Significant at a 95% level or better. Standard Errors in parantheses.

Industry 5 - Transportation, Communications & Utilities

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	-.272*	(.006)	-.075*	(.002)	-.468*	(.013)	-.580*	(.015)
$\frac{1}{t}$	-.254*	(.025)	.056*	(.021)	-.325*	(.013)	-.138*	(.023)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.439*	(.012)	-.439*	(.012)	-.439*	(.012)	-.439*	(.012)
$\sigma_5=\frac{1}{(1-\rho)}$	2.27							
No. Obs. 92								

Industry 6 - Wholesale and Retail Trade

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	-.186*	(.003)	-.165*	(.003)	-.229*	(.004)	-.297*	(.008)
$\frac{1}{t}$	-.266*	(.021)	.068*	(.022)	-.090*	(.020)	-.078*	(.019)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.332*	(.012)	-.332*	(.012)	-.332*	(.012)	-.332*	(.012)
$\sigma_6=\frac{1}{(1-\rho)}$	3.01							
No. Obs. 92								

Industry 7 - Finance, Insurance and Real Estate

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	-.172*	(.003)	-.042*	(.004)	-.507*	(.009)	-.531*	(.014)
$\frac{1}{t}$	-.377*	(.027)	.027	(.023)	-.049	(.035)	-.270*	(.070)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.559*	(.011)	-.559*	(.011)	-.559*	(.011)	-.559*	(.011)
$\sigma_7=\frac{1}{(1-\rho)}$	1.78							
No. Obs. 88								

Industry 8 - Services

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	-.071*	(.002)	.227*	(.004)	-.076*	(.002)	-.333*	(.004)
$\frac{1}{t}$	-.135*	(.019)	.105*	(.017)	.022	(.018)	.001	(.021)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.607*	(.007)	-.607*	(.007)	-.607*	(.007)	-.607*	(.007)
$\sigma_8 = \frac{1}{(1-\rho)}$	1.64							
No. Obs. 92								

Note: * Significant at a 95% level or better. Standard Errors in parantheses.

Table 6: NL2SLS with cross-equation restrictions for the estimation of the impact of non-neutral technological change, using R&D

Industry 1 - Agriculture, Forestry and Fisheries

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.361*	(.044)	.111*	(.026)	-.334*	(.041)	-.166*	(.021)
$\frac{1}{RD}$	-.745*	(.137)	-.479*	(.063)	.065	(.108)	-.013	(.034)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.150*	(.024)	-.150*	(.024)	-.150*	(.024)	-.150*	(.024)
$\sigma_1 = \frac{1}{(1-\rho)}$	6.66							
No. Obs. 87								

Industry 2 – Mining

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.371*	(.060)	-.154*	(.018)	.209*	(.031)	.033	(.045)
$\frac{1}{RD}$	-.243	(.176)	.005	(.055)	-.287*	(.108)	.389*	(.100)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.103*	(.018)	-.103*	(.018)	-.103*	(.018)	-.103*	(.018)
$\sigma_2 = \frac{1}{(1-\rho)}$	9.7							
No. Obs. 72								

Industry 3 - Construction

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.271*	(.042)	-.029*	(.012)	-.258*	(.034)	-.335*	(.048)
$\frac{1}{RD}$	-.784*	(.132)	-.267*	(.029)	-.535*	(.048)	-.101*	(.048)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.183*	(.019)	-.183*	(.019)	-.183*	(.019)	-.183*	(.019)
$\sigma_3 = \frac{1}{(1-\rho)}$	5.46							
No. Obs. 92								

Industry 4 - Manufacturing

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.315*	(.041)	-.140*	(.005)	-.288*	(.007)	-.261*	(.007)
$\frac{1}{RD}$	-.990*	(.127)	.529	(.022)	-.529*	(.022)	.033*	(.012)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.389*	(.014)	-.389*	(.014)	-.389*	(.014)	-.389*	(.014)
$\sigma_4 = \frac{1}{(1-\rho)}$	2.57							
No. of Obs. 92								

Note: * Significant at a 95% level or better. Standard Errors in parantheses.

Industry 5 - Transportation, Communications & Utilities

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.330*	(.040)	-.130*	(.006)	-.270*	(.016)	-.370*	(.020)
$\frac{1}{RD}$	-.756*	(.124)	.107*	(.021)	-.364*	(.040)	-.349*	(.028)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.328*	(.018)	-.328*	(.018)	-.328*	(.018)	-.328*	(.018)
$\sigma_5 = \frac{1}{(1-\rho)}$	3.04							
No. Obs. 92								

Industry 6 - Wholesale and Retail Trade

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.351*	(.037)	-.170*	(.006)	-.103*	(.009)	-.174*	(.011)
$\frac{1}{RD}$	-.651*	(.116)	-.037*	(.018)	-.388*	(.020)	-.087*	(.016)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.153*	(.017)	-.153*	(.017)	-.153*	(.017)	-.153*	(.017)
$\sigma_6 = \frac{1}{(1-\rho)}$	6.53							
No. Obs. 92								

Industry 7 - Finance, Insurance and Real Estate

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.428*	(.044)	-.125*	(.008)	-.378*	(.019)	-.233*	(.030)
$\frac{1}{RD}$	-.812*	(.136)	.041*	(.024)	-.020	(.042)	-.378*	(.080)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.346*	(.020)	-.346*	(.020)	-.346*	(.020)	-.346*	(.020)
$\sigma_7 = \frac{1}{(1-\rho)}$	2.89							
No. Obs. 88								

Industry 8 - Services

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.425*	(.038)	.113*	(.007)	-.101*	(.004)	-.330*	(.009)
$\frac{1}{RD}$	-.603*	(.116)	.192*	(.018)	-.043*	(.014)	-.015	(.024)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.542*	(.012)	-.542*	(.012)	-.542*	(.012)	-.542*	(.012)
$\sigma_8 = \frac{1}{(1-\rho)}$	1.84							
No. Obs. 92								

Note: * Significant at a 95% level or better. Standard Errors in parantheses.

Table 7: NL2SLS with cross-equation restrictions for the estimation of the impact of non-neutral technological change, taking into account the unexplained gender wage gap (discrimination), using RD

Industry 1 - Agriculture, Forestry and Fisheries

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	-.207*	(.022)	.015	(.027)	-.341*	(.025)	-.176*	(.023)
$\frac{1}{RD}$	-.051	(.073)	-.180*	(.067)	.065	(.113)	-.042	(.045)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.192*	(.023)	-.192*	(.023)	-.192*	(.023)	-.192*	(.023)
$\sigma_1 = \frac{1}{(1-\rho)}$	5.20							
No. Obs. 87								

Industry 2 – Mining

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	-.107*	(.025)	-.132*	(.022)	.114*	(.046)	-.052	(.040)
$\frac{1}{RD}$	.002	(.070)	.048	(.066)	-.244*	(.105)	.270*	(.089)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.132*	(.015)	-.132*	(.015)	-.132*	(.015)	-.132*	(.015)
$\sigma_2 = \frac{1}{(1-\rho)}$	7.57							
No. Obs. 72								

Industry 3 - Construction

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	-.126*	(.011)	-.018	(.012)	-.250*	(.031)	-.299*	(.029)
$\frac{1}{RD}$	-.484*	(.048)	-.202*	(.032)	-.439*	(.044)	-.114*	(.043)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.175*	(.018)	-.175*	(.018)	-.175*	(.018)	-.175*	(.018)
$\sigma_3 = \frac{1}{(1-\rho)}$	5.71							
No. Obs. 92								

Industry 4 - Manufacturing

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	-.121*	(.007)	-.126*	(.008)	-.262*	(.008)	-.238*	(.008)
$\frac{1}{RD}$	-.674*	(.027)	.036	(.020)	-.502*	(.025)	.072*	(.019)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.384*	(.014)	-.384*	(.014)	-.384*	(.014)	-.384*	(.014)
$\sigma_4 = \frac{1}{(1-\rho)}$	2.60							
No. of Obs. 92								

Note: * Significant at a 95% level or better. Standard Errors in parantheses.

Industry 5 - Transportation, Communications & Utilities

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.069*	(.013)	-.093*	(.002)	-.460*	(.013)	-.578*	(.016)
$\frac{1}{RD}$	-.367*	(.013)	.031*	(.028)	-.321*	(.028)	-.163*	(.024)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.417*	(.013)	-.417*	(.013)	-.417*	(.013)	-.417*	(.013)
$\sigma_5 = \frac{1}{(1-\rho)}$	2.39							
No. Obs. 92								

Industry 6 - Wholesale and Retail Trade

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.131*	(.011)	-.189*	(.002)	-.266*	(.005)	-.309*	(.010)
$\frac{1}{RD}$	-.389*	(.082)	.048*	(.015)	-.122*	(.017)	-.086*	(.014)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.307*	(.014)	-.307*	(.014)	-.307*	(.014)	-.307*	(.014)
$\sigma_6 = \frac{1}{(1-\rho)}$	3.25							
No. Obs. 92								

Industry 7 - Finance, Insurance and Real Estate

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.182*	(.013)	-.054*	(.004)	-.537*	(.009)	-.545*	(.014)
$\frac{1}{RD}$	-.507*	(.098)	.018	(.020)	-.030	(.036)	-.275*	(.070)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.557*	(.011)	-.557*	(.011)	-.557*	(.011)	-.557*	(.011)
$\sigma_7 = \frac{1}{(1-\rho)}$	1.79							
No. Obs. 88								

Industry 8 - Services

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.249*	(.011)	.201*	(.007)	-.112*	(.001)	-.358*	(.004)
$\frac{1}{RD}$	-.280*	(.083)	.192*	(.018)	.013	(.011)	-.018	(.018)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.600*	(.007)	-.600*	(.007)	-.600*	(.007)	-.600*	(.007)
$\sigma_8 = \frac{1}{(1-\rho)}$	1.66							
No. Obs. 92								

Note: * Significant at a 95% level or better. Standard Errors in parantheses.

Summary of results:

Occ1	$\frac{1}{t}$	$\frac{1}{t}\&d$	Occ2	$\frac{1}{t}$	$\frac{1}{t}\&d$	Occ3	$\frac{1}{t}$	$\frac{1}{t}\&d$	Occ4	$\frac{1}{t}$	$\frac{1}{t}\&d$
Ind 1	-.404*	-.176*	Ind 1	-.064*	.110*	Ind 1	.168*	.166*	Ind 1	-.049*	-.047
2	-.408*	-.138*	2	-.003	-.038	2	-.322*	-.212*	2	.121	.076
3	-.390*	-.308*	3	-.133*	-.113*	3	-.285*	-.234*	3	-.081*	-.087*
4	-.413*	-.315*	4	-.028*	-.226*	4	-.245*	-.418*	4	.003	-.331*
5	-.367*	-.254*	5	.031*	.056*	5	-.321*	-.325*	5	-.163*	-.138*
6	-.389*	-.266*	6	.048	.068*	6	-.122*	-.090*	6	-.086*	-.078*
7	-.507*	-.377*	7	.018	.027	7	-.030	-.049	7	-.275*	-.270*
8	-.280*	-.135*	8	.083*	.105*	8	.013	.022	8	-.018	.001

Occ1	$\frac{1}{RD}$	$\frac{1}{RD}\&d$	Occ2	$\frac{1}{RD}$	$\frac{1}{RD}\&d$	Occ3	$\frac{1}{RD}$	$\frac{1}{RD}\&d$	Occ4	$\frac{1}{RD}$	$\frac{1}{RD}\&d$
Ind 1	-.745*	-.051	Ind 1	-.479*	-.180*	Ind 1	.065	.065	Ind 1	-.013	-.042
2	-.243	.002	2	.005	.048	2	-.287*	-.244*	2	.389*	.270*
3	-.784*	-.484*	3	-.267*	-.202*	3	-.535*	-.439*	3	-.101*	-.114*
4	-.990*	-.674*	4	.529*	.036	4	-.287	-.502*	4	.033*	.072*
5	-.756*	-.367*	5	.107*	.031*	5	-.364*	-.321*	5	-.349*	-.163*
6	-.651*	-.389*	6	-.037*	.048*	6	-.388*	-.122*	6	-.087*	-.086*
7	-.812*	-.507*	7	.041*	.018	7	-.020	-.030	7	-.378*	-.275*
8	-.603*	-.280*	8	.192*	.192*	8	-.043*	.013	8	-.015	-.018

Data Appendix

The CPS is a monthly survey of about 60,000 households. An adult (the reference person) at each household is asked to report on the activities of all other persons in the household. There is a record in the file for each adult person. The universe is the adult non-institutional population. Each household entering the CPS is administered 4 monthly interviews, then ignored for 8 months, then interviewed again for 4 more months. If the occupants of a dwelling unit move, they are not followed, rather the new occupants of the unit are interviewed. Since 1979 only households in months 4 and 8 have been asked their usual weekly earnings/usual weekly hours. These are the outgoing rotation groups, and each year the Bureau of Labor Statistics (BLS) gathers all these interviews together into a single Merged Outgoing Rotation Group File. A consequence of this construction is that an individual appears only once in any file year, but may reappear in the following year. Only hourly or weekly earnings are recorded. The sample is stratified to provide better estimates for minorities and smaller political jurisdictions. Weights are provided for the preparation of descriptive values and tabulations. All persons 16 years of age or over are included in the extracts.