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Technological Change and Gender Wage Gaps in the US Service Industry

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This paper investigates the relation between advances in technology and trends in the gender wage gaps in the US service industry. Using quarterly US Current Population Survey data on employment and wages by four major occupations between 1979 and 2001, the paper estimates a constant elasticity of substitution production function (CES) that incorporates male and female labor inputs, a non-labor input and a productivity parameter function that captures non-neutral technological change. The model is estimated by two stage least squares (2SLS) with cross-equation restrictions. The results reveal a narrowing effect of technological change on the female-male wages for the highest skill level occupation (managerial, professional occupations). This effect is robust to controlling for the unexplained gender wage gap and to using direct measures of technological change. The effect of technological change on the gender wage gaps for the other skill levels tends to diminish or disappear altogether once changes in unexplained gender wage gaps are adjusted for. The results highlight the importance of considering the unexplained gender wage gaps in examining the effect of technological change on the gender wage gaps.*

I. Introduction

The US labor market has experienced a dramatic increase in wage inequality from the late 1970's into the 1990's, increase attributed mainly to non-neutral, biased technological change (BERMAN et al. [1994]). The major exception from the pattern of a widening wage structure has been the considerable narrowing of wage gaps between men and women during the 1980's and 1990's. After a period of three decades of little change, starting with the late 1970's the gender wage gap began to narrow at a rapid pace through the 1980's, and then slowed somewhat during the 1990's (DATTA GUPTA et. al, [2006]; BLAU and KAHN, [2006]). According to data from the U.S. Bureau of Labor Statistics, the weekly earnings of full-time female workers increased from about 59 percent in 1979 to 77.5 percent of what their male counterparts earned in 1999. There is a large literature in labor economics that attempts to explain the trends in gender wage gaps (O'NEILL and POLACHEK [1993], BLAU and KAHN [1994], [1997], [2000] and [2006]). However, in the light of the recent changes in the wage structure, the question of

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the link between technological change and the narrowing of the gender wage gap is still open (CARD and DINARDO [2002]). ALLEN [2001] reports evidence on how technological change is related to changes in wage gaps by schooling, experience and gender. Specifically, it reports that the gender gap narrowed more in industries that most intensively used high-tech capital in 1979. This result suggests that there might be a relation between the narrowing of the gender wage gap and technological change.

In this paper we investigate directly the effect of non-neutral technological change on the documented narrowing of the gender wage gaps in the US service industry over the period 1979-2001. The service industry accounts for 55 percent of economic activity in the US[1]. Specifically, the service industry accounted for 42.52 percent of the private (non-government) sector of the US economy by hours worked by full-time and part-time employees in 2001.[2] By comparison, the next most important industry in the US economy is the manufacturing industry, with 16.19 percent of the hours worked by full-time and part-time employees in the US private sector in 2001.

Our examination of the effect of technological change on the gender wage gaps uses a constant elasticity of substitution production function that incorporates male and female labor inputs, a non-labor input, and a productivity parameter function that captures non-neutral technological change. We use quarterly Current Population Surveys (CPS) employment and wage data from 1979 to 2001 to conduct our analysis at a more disaggregated level than in earlier work by partitioning the labor inputs by level of skill (occupation). In addition, in a departure from the previous literature, our analysis of the effects of technological change on the narrowing of the gender wage gap incorporates non-productivity related (unexplained) gender wage gaps. If the gender wage gap is evolving differently over time for the different occupational categories, we argue that changes in technological change can explain some of that variation. As economists have long suspected, technological change can affect differently the return to skill of male and female workers, including unobserved skills that drive some of the unexplained gender wage gap. However, employers' taste towards discrimination has been considered for a long time as a standard source of the unexplained gender wage differences. We show that there can be a confounding effect between non-neutral technological change and changes in the unexplained gender wage gap as labor market discrimination. Therefore failure to consider changes in the labor market discrimination could lead to bias in the estimated elasticity of factor substitution as well as in the estimation of the effects of non-neutral technological change on the gender wage gap. We do not attempt here to settle the question of how much of the unexplained wage gap arose from labor market discrimination.

II. Conceptual Framework

II.*1* *A CES Production Function with Non-neutral Technological Change*

To illustrate the concept of non-neutral technological change in relation to gender wage gaps, assume that non-neutral technological change can be modeled as a shift in an industry-wide

1. See the Quarterly Services Survey and the Sevice Annual Survey, conducted by the US Census Bureau.
2. Data come from the National Income and Product Accounts Table 6.9D, provided by the Bureau of Economic Analysis of the US Department of Commerce.

production technology that is characterized as a quarterly constant elasticity of substitution (CES) production function[3] of the following form:

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

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

The marginal products can be expressed as

$$MP_{L_{jt}} = \phi A_t^{\frac{\rho}{\phi}}\alpha_{jt}L_{jt}^{\rho-1}Q_t^{1-\frac{\rho}{\phi}} \tag{1}$$

and

$$MP_{Kt} = \phi A_t^{\frac{\rho}{\phi}}\left[1-\sum_{j=1}^{J}\alpha_{jt}\right]K_t^{\rho-1}Q_t^{1-\frac{\rho}{\phi}}. \tag{2}$$

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

$$\frac{MP_{L_{jt}}}{MP_{L_{ht}}} = \frac{w_{jt}}{w_{ht}},\ j \neq h \tag{3}$$

and

$$\frac{MP_{Kt}}{MP_{Ljt}} = \frac{r_t}{w_{jt}}. \tag{4}$$

Upon substituting (1) and (2) into (3) and (4) and normalizing relative to the h^{th} labor input (i.e. L_{ht} , and w_{ht}), one obtains

$$\frac{\alpha_{jt}L_{jt}^{\rho-1}}{\alpha_{ht}L_{ht}^{\rho-1}} = \frac{w_{jt}}{w_{ht}},\ j \neq h.$$

Taking the log of the above relations yields the following set of inverse relative input demand functions:

$$\ln\left(\frac{w_{jt}}{w_{ht}}\right) = \ln\left(\frac{\alpha_{jt}}{\alpha_{ht}}\right) + (\rho-1)\ln\left(\frac{L_{jt}}{L_{ht}}\right),\ j \neq h \tag{5}$$

3. Using Cobb-Douglas or Leontief production technologies, as special cases of the CES production function, would not capture biases in estimating the factor elasticity of substitution resulting from ignoring changes in unexplained gender wage gaps. For these production technologies, the elasticity of substitution is constrained to unity or zero.

and

$$\ln\left(\frac{r_t}{w_{ht}}\right) = \ln\left(\frac{1}{\alpha_{ht}}\left[1-\sum_{j=1}^{J}\alpha_{jt}\right]\right) + (\rho-1)\ln\left(\frac{K_t}{L_{ht}}\right). \tag{6}$$

The specification of the α_{jt} functions is given by a multinomial logit form:

$$\alpha_{jt} = \frac{e^{\alpha_{j0}+\alpha_{j1}\left(\frac{1}{t}\right)+\epsilon_{jt}}}{1+\sum_{j=1}^{J} e^{\alpha_{j0}+\alpha_{j1}\left(\frac{1}{t}\right)+\epsilon_{jt}}},\ j = 1,\ldots,J \tag{7}$$

and

$$\alpha_{J+1,t} = 1-\sum_{j=1}^{J}\alpha_{jt} = \frac{1}{1+\sum_{j=1}^{J} e^{\alpha_{j0}+\alpha_{j1}\left(\frac{1}{t}\right)+\epsilon_{jt}}}, \tag{8}$$

where $0 < \alpha_{jt} < 1$, $\sum_{j=1}^{J+1}\alpha_{jt} = 1$ (the last restriction being necessary for the identification of the $\alpha's$), and ϵ_{jt} is a random error term distributed $(0, \sigma_\epsilon^2)$.

Given the specification of the α_{jt} functions, equations (5) and (6) become stochastic equations of the following form:

$$\ln\left(\frac{w_{jt}}{w_{ht}}\right) = \beta_{jh0} + \beta_{jh1}\frac{1}{t} + (\rho-1)\ln\left(\frac{L_{jt}}{L_{ht}}\right) + \epsilon_{jht},\ j \neq h, \tag{9}$$

and

$$\ln\left(\frac{r_t}{w_{ht}}\right) = \beta_{kh0} + \beta_{kh1}\frac{1}{t} + (\rho-1)\ln\left(\frac{K_t}{L_{ht}}\right) + \epsilon_{kht}, \tag{10}$$

where $\beta_{jh0} = \alpha_{j0} - \alpha_{h0}$, $\beta_{jh1} = \alpha_{j1} - \alpha_{h1}$, $\epsilon_{jht} = \epsilon_{jt} - \epsilon_{ht}$ with $j \neq h$, and $j = 1, \ldots, J$ for equation (9), and $\beta_{kh0} = -\alpha_{h0}$, $\beta_{kh1} = -\alpha_{h1}$, $\epsilon_{kht} = -\epsilon_{ht}$ for equation (10). In this specification, the effect of non-neutral technological change is captured by the coefficients on $1/t$. With the above specification the α_{jt} functions capture the savings in one labor or non-labor input relative to another, while the inverse of t insures a bounded measure of such savings.[4] The parameter $(\rho - 1)$ will allow us to estimate the elasticity of substitution between factors of production since the factor elasticity of substitution, σ, is equal to $1/(1-\rho)$.

II. 2 *A New Dimension: Unexplained Wage Differences*

The issue of unexplained wage differences between male and female workers has been extensively documented in the labor literature and thus it cannot be ignored as a potential major factor that shapes the gender wage gap. We do not attempt here to settle the question of how much of

4. The choice of $\frac{1}{t}$ instead of t as a functional form in the production function is justified by the desire to avoid indefinitely diverging relative wages.

the unexplained wage gap arose from labor market discrimination. Our objective is concerned with proposing a framework for incorporating the unexplained wage differences component. This framework allows one to measure any potential unexplained wage differences and to control for any potential confounding effect between biased technological change and changes in the unexplained gender gap.

To generalize BECKER's [1971] decomposition of the relative wage gap between groups of workers into marginal product and unexplained wage differences components, let the wage w_{jt}^m of male workers in quarter t, occupation j be equated to the corresponding marginal product:

$$w_{jt}^m = MP_{L_{jt}}^m.$$

Let the wage w_{jt}^f of female workers in quarter t, occupation j be equated to the corresponding marginal product, discounted by an unexplained wage differences index (d_{jt}):

$$w_{jt}^f = \frac{MP_{Ljt}^f}{(1+d_{jt})}.$$

This is a normalizing assumption that allows for the identification of discounted relative productivities of female workers in each occupation. It is plausible to expect that the unexplained wage differential for female workers in any given occupation (d_{jt}) is correlated with t and L_{jt}^f / L_{jt}^m. Certainly in the Becker framework the extent of employer discrimination depends on the relative supply of the discriminated against group. Failure to take account of the unexplained gap could lead to bias in the estimates of the effects of technological change and the elasticity of substitution. Below we specify the relative wage equations among the different categories of labor inputs and the non-labor input.

Our model specifies a non labor input plus four occupational categories comprised of eight occupation/gender labor inputs.

The relative wage equations for female workers in occupation j, (relative to male workers in occupation h) will reflect potential unexplained wage differences, and can be written as

$$\ln\left(\frac{w_{jt}^f}{w_{ht}^m}\right) = \ln\left(\frac{MP_{jt}^f}{MP_{ht}^m}\right) - \ln\left(1+d_{jt}\right). \tag{11}$$

Note that (11) implies:

$$\begin{aligned}\ln\left(\frac{w_{jt}^f}{w_{ht}^m}\right) + \ln(1+d_{jt}) &= \ln\left(\frac{MP_{jt}^f}{MP_{ht}^m}\right) \\ &= \beta_{jh0}^{fm} + \frac{\beta_{jh1}^{fm}}{t} + (\rho-1)\ln\left(\frac{L_{jt}^f}{L_{ht}^m}\right) + \epsilon_{jht}^{fm},\end{aligned} \tag{12}$$

where $\beta^{fm}_{jh0} = \alpha^{f}_{j0} - \alpha^{m}_{h0}$, $\beta^{fm}_{jh1} = \alpha^{f}_{j1} - \alpha^{m}_{h1}$, and $\epsilon^{fm}_{jht} = \epsilon^{f}_{jt} - \epsilon^{m}_{ht}$ for $j, h = 1, \ldots, 4$. The α parameters for males and females are defined by equation (7).

The wage equations for female workers in occupation j, relative to the wage of female workers in occupation h, with $j \neq h$ can be written as

$$\ln\left(\frac{w^{f}_{jt}}{w^{f}_{ht}}\right) = \ln\left(\frac{MP^{f}_{jt}}{MP^{f}_{ht}}\right) + \ln(1 + d_{ht}) - \ln(1 + d_{jt}),$$

which implies:

$$\begin{aligned}\ln\left(\frac{w^{f}_{jt}}{w^{f}_{ht}}\right) - \ln(1 + d_{ht}) + \ln(1 + d_{jt}) &= \ln\left(\frac{MP^{f}_{jt}}{MP^{f}_{ht}}\right) \\ &= \beta^{ff}_{jh0} + \frac{\beta^{ff}_{jh1}}{t} + (\rho - 1)\ln\left(\frac{L^{f}_{jt}}{L^{f}_{ht}}\right) + \epsilon^{ff}_{jht},\end{aligned} \tag{13}$$

where $\beta^{ff}_{jh0} = \alpha^{f}_{j0} - \alpha^{f}_{h0}$, $\beta^{ff}_{jh1} = \alpha^{f}_{j1} - \alpha^{f}_{h1}$, and $\epsilon^{ff}_{jht} = \epsilon^{f}_{jt} - \epsilon^{f}_{ht}$ for $j, h = 1, \ldots, 4$.

The wage equations for female workers in occupation j, relative to the non-labor input can be expressed as

$$\ln\left(\frac{w^{f}_{jt}}{r_t}\right) = \ln\left(\frac{MP^{f}_{jt}}{r_t}\right) - \ln(1 + d_{jt}),$$

which implies

$$\begin{aligned}\ln\left(\frac{w^{f}_{jt}}{r_t}\right) + \ln(1 + d_{jt}) &= \ln\left(\frac{MP^{f}_{jt}}{r_t}\right) \\ &= \beta^{f}_{jk0} + \frac{\beta^{f}_{jk1}}{t} + (\rho - 1)\ln\left(\frac{L^{f}_{jt}}{K_t}\right) + \epsilon^{f}_{jkt},\end{aligned} \tag{14}$$

where $\beta^{f}_{jk0} = \alpha^{f}_{j0}$, $\beta^{f}_{jk1} = \alpha^{f}_{j1}$, and $\epsilon^{f}_{jkt} = \epsilon^{f}_{jt}$ for $j = 1, \ldots, 4$.

The wage equations for male workers in occupation j, relative to the wage of male workers in occupation h, with $j \neq h$ can be written as

$$\begin{aligned}\ln\left(\frac{w^{m}_{jt}}{w^{m}_{ht}}\right) &= \ln\left(\frac{MP^{m}_{jt}}{MP^{m}_{ht}}\right) \\ &= \beta^{mm}_{jh0} + \frac{\beta^{mm}_{jh1}}{t} + (\rho - 1)\ln\left(\frac{L^{m}_{jt}}{L^{m}_{ht}}\right) + \epsilon^{mm}_{jht},\end{aligned} \tag{15}$$

where $\beta^{mm}_{jh0} = \alpha^{m}_{j0} - \alpha^{m}_{h0}$, $\beta^{mm}_{jh1} = \alpha^{m}_{j1} - \alpha^{m}_{h1}$, and $\epsilon^{mm}_{jht} = \epsilon^{m}_{jt} - \epsilon^{m}_{ht}$ for $j, h = 1, \ldots, 4$. Note that in the wage equation above there is no unexplained wage differences component for males.

Finally, the wage equations for male workers in occupation j, relative to the non-labor input can be expressed as

$$\ln\left(\frac{w^{m}_{jt}}{r_t}\right) = \ln\left(\frac{MP^{m}_{jt}}{r_t}\right) = \beta^{m}_{jk0} + \frac{\beta^{m}_{jk1}}{t} + (\rho - 1)\ln\left(\frac{L^{m}_{jt}}{K_t}\right) + \epsilon^{m}_{jkt}, \tag{16}$$

where $\beta^{m}_{jk0} = \alpha^{m}_{j0}$, $\beta^{m}_{jk1} = \alpha^{m}_{j1}$, and $\epsilon^{m}_{jkt} = \epsilon^{m}_{jt}$ for $j = 1, \ldots, 4$.

To estimate equations (12), (13), (14), (15), (16) we first estimate the unexplained gender wage gap, $\ln(1 + d_{jt})$ from micro data as shown below, and continue with instrumental variable estimations.

II. 3 *Non-neutral Technological Change, Controlling for Skills and Potential Unexplained Wage Differences*

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 unexplained wage differences. By using micro data on individual characteristics (schooling, potential experience, potential experience squared), aggregated each quarter by occupation, the unexplained gender wage gap can be estimated.

Consider first the wage equation for a male worker l, in occupation j, quarter t,

$$\ln(w^{m}_{jtl}) = X^{m}_{jtl}\beta^{m}_{jt} + \upsilon^{m}_{jtl}, \tag{17}$$

where X^{m}_{jtl} is the vector of individual characteristics of male workers.

Similarly, consider the wage equation for a female worker l, in occupation j, quarter t,

$$\ln(w^{f}_{jtl}) = X^{f}_{jtl}\beta^{f}_{jt} + \upsilon^{f}_{jtl}, \tag{18}$$

where X^{f}_{jtl} is the vector of individual characteristics of female workers.

By using the estimated coefficients of the male and female workers' wage equations, the average (log) wage gap between female and male workers can be decomposed according to OAXACA [1973] as

$$\ln(w^{m}_{jt}) - \ln(w^{f}_{jt}) = (\overline{X}^{m}_{jt} - \overline{X}^{f}_{jt})\beta^{m}_{jt} + \overline{X}^{f}_{jt}(\beta^{m}_{jt} - \beta^{f}_{jt}),$$

where the first right hand side term represents the wage gap due to differences in skills and the second term represents the unexplained wage gap.

Using the decomposition above, a measure of unexplained differences can be obtained as

$$\ln(1+d_{jt}) = \overline{X}^{f}_{jt}(\beta^{m}_{jt} - \beta^{f}_{jt}) \\ = \ln\left(\frac{w^{m}_{jt}}{w^{f}_{jt}}\right) - (\overline{X}^{m}_{jt} - \overline{X}^{f}_{jt})\hat{\beta}^{m}_{jt}, \tag{19}$$

where $\overline{X}^{f(m)}_{jt}$ is the sample weighted average of female (male) workers' characteristics, $\overline{X}^{f(m)}_{jt} = \Sigma_{l_f}(X^{f(m)}_{jtl}).weight^{f(m)}_{jtl}$, where $weight^{f(m)}_{jtl}$ is the sampling weight.[5] In the relative inverse demand (marginal product) equations specified by (12), (13), and (14) that include the unexplained gap terms, we substitute the calculated values of $\ln(1 + d_{jt})$ as per equation (19).

III. Data Description

III.1 Data on Employment and Wages

To empirically investigate the impact of technological change on the gender wage gaps in the US service industry, data from the US Current Population Survey (CPS) on quarterly hourly wage and employment in the service industry are used for the years 1979 to 2001. The data source is the National Bureau of Economic Research (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 wage data are used for full time employees, 16 years or over, aggregated quarterly by gender and occupation using the individual weights provided by the CPS. The wage equations corresponding to (17) and (18) were estimated from individual monthly data pooled for each quarter.

The wage data are hourly wages for full-time workers. In the sample, the overall ratio of women's wages to men's wages in the US service industry changes from 0.60 at the beginning of 1979 to 0.74 at the end of 1989, and to 0.76 at the end of 1999. The narrowing trend in the 1980's until the late 1990's is consistent with trends reported in previous work.[6]

Data on wages and employment are aggregated at the 2-digit Standard Industrial Classification (SIC) code industry level for the service industry, and four major occupations following the Bureau of Labor Statistics (BLS) classification of major occupational categories. TABLE I lists the occupation variables. TABLE II provides a description of the variables used in the estimations, and TABLE III provides summary statistics.

5. Alternatively, the unexplained gap can be estimated by using the method proposed by OAXACA and RANSOM [1994]. First, a common wage structure is estimated for both male and female workers:
$ln\left(w_{jtk}\right) = X_{jtk}\tilde{\beta}_{jt} + \upsilon_{jt}$. Then, the measure of the unexplained gap is obtained as:
$ln\left(1+d_{jt}\right) = \overline{X}^{m}_{jt}(\beta^{m}_{jt} - \tilde{\beta}_{jt}) + \overline{X}^{f}_{jt}(\tilde{\beta}_{jt} - \beta^{f}_{jt})$
where $\overline{X}^{m}_{jt}$ is the sample average, $\overline{X}^{m}_{jt} = \sum_{l_m}(X^{m}_{jtl}).weight^{m}_{jtl}$
and $\overline{X}^{f}_{jt}$ is the sample average, $\overline{X}^{f}_{jt} = \sum_{l_f}(X^{f}_{jtl}).weight^{f}_{jtl}$. However, this alternative requires a larger number of estimations, thus it is more costly.
6. O'NEIL and POLACHEK [1993], BLAU and KAHN [1994], BLAU and KAHN [2000], and DATTA GUPTA et al [2006].

TABLE I. — Definition of Occupation Variables

Occupational Categories	
Occ 1	Managerial and Professional Specialty
Occ 2	Technical, Sales and Administrative Support
Occ 3	Service Occupations and Precision Production, Craft and Repair
Occ 4	Operators, Fabricators and Laborers, Farming, Forestry and Fishing

TABLE II. — Definition of Variables

Variable	Description
w_{jt}^{f}	Hourly wage of full time female employees, occupation j, quarter t [dollars]
w_{jt}^{m}	Hourly wage of full time male employees, occupation j, quarter t [dollars]
L_{jt}^{f}	Full time female employees, occupation j, quarter t [thousands]
L_{jt}^{m}	Full time male employee, occupation j, quarter t [thousands]
r_t	Non-labor Input factor price in quarter t
K_t	Non-labor Input, in quarter t [thousand 2000 dollars]
i_t	3-month T-bill rate
RD_t	Total R&D expenditure for quarter t [million 2000 dollars]

TABLE III. — Summary Statistics of Main Variables

Variable	Mean	Std. Dev.	No.Obs.
$\frac{w_{1t}^{f}}{w_{1t}^{m}}$	0.791	0.164	92
$\frac{w_{2t}^{f}}{w_{2t}^{m}}$	0.783	0.189	92
$\frac{w_{3t}^{f}}{w_{3t}^{m}}$	0.786	0.431	87
$\frac{w_{4t}^{f}}{w_{4t}^{m}}$	0.895	0.070	92
L_{1t}^{f}	1,694,543	374,661.6	92
L_{2t}^{f}	1,195,887	157,752.6	92
L_{3t}^{f}	908,408.7	96,894.8	92
L_{4t}^{f}	85,589.4	13,714.7	92
L_{1t}^{m}	1,602,240	240,879.3	92
L_{2t}^{m}	343,033.3	77,278.38	92
L_{3t}^{m}	794,278.2	83,561.8	92
L_{4t}^{m}	231,720.2	39,422.2	92
r_t	0.055	0.006	92
K_t	58,448.3	28,594.7	92
i_t	0.016	0.007	92
RD_t	33,426	8,417.57	92

Data source: 1979-2001 Quarterly CPS data and NSF R&D data.

III.*2 Data on Non-labor Factor and Factor Price*

Data for the non-labor input come primarily from the National Income and Product Accounts (NIPA) tables of the Bureau of Economic Analysis (BEA). The series on the non-labor input K_t was obtained from recursive equations, given initial conditions for K_t, and a calculated rate of capital depreciation δ_t. To obtain a series on r_t, the user cost of capital is used.

Here we describe how the data on the non-labor factor were obtained. We start with the following accounting relation:

$$P_t Q_t = w_t L_t + r_t K_t, \tag{20}$$

where data for P_tQ_t were obtained from the NIPA Table 6.1, National Income without Capital Consumption Adjustment by Industry, and data on w_tL_t came from BEA Table SQ7 (State Quarterly Income Estimates). Ideally, one uses value added data for P_tQ_t when such data are available. Alternatively P_tQ_t can be measured by the value of production after subtracting the cost of raw materials or energy. Given that in the Service sector the cost of raw materials is not a significant component the calculation of K_t using National Income without Capital Consumption Adjustment data from the NIPA tables is a reasonable solution. Data on $\delta_t r_{t-1} K_{t-1}$ can be retrieved from NIPA Tables 6.13 and 6.22, Non-corporate and Corporate Capital Consumption Allowances by Industry, 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. Accordingly δ_t can be backed out for our industry of interest.

Assuming a normal rate of return, the user cost of capital can be calculated as follows:

$$r_t = (i_t + \delta_t) pd_t,$$

where i_t is the quarterly 3-month T-bill rate from the Federal Reserve Statistical Release of Historical Data[7], δ_t is the depreciation rate, 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 is obtained residually from (20):

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

This construction of K_t ensures internal consistency of the data.

IV. Empirical Issues

IV.*1 Estimation Strategy*

Given the conceptual framework proposed above, the empirical investigation of the effect of non-neutral technological change on the gender wage gaps in the US service industry involves estimating a system of equations as described by (9) and (10) without adjustment for movements

7. Specifically, the i_t rates used in our paper are 3-month Treasury bill secondary market rates, reported monthly as annualized rates. We used quarterly averages of the annualized monthly rates, and brought these averages to quarterly interest rates by using $i_t = [(1 + i_{at})^{1/4} - 1]$, where i_{at} is the quarterly average of the annualized monthly rates.

in the unexplained gender wage gap, and by (12), (13), (14), (15), and (6) when movements in the unexplained gender wage gaps are controlled for.

The cross-equations restrictions on the ρ parameter result from the functional form of the production function which implies an elasticity of substitution that does not vary with time, and is the same for all pairs of labor, non-labor factors. Thus, $(\rho - 1)$ will be restricted to be the same across all equations.[8] Our identification strategy will have to take into account cross-equation restrictions on ρ and the endogeneity of the relative input ratios.

In the literature, the standard approach to estimating a constant elasticity of substitution specifies the factor intensity as the dependent variable and the relative factor prices as the independent variable. Thus, the relative factor prices are usually considered exogenous as firms are assumed to be competitive in the factor market. At the industry level however, the factor price ratios could be considered endogenous. Since the focus of this paper is on the impact of technological change on gender wage gaps in the service industry, the factor price ratio is normalized as the dependent variable. Hence, the factor intensity variables are endogenous. Consequently, consistent estimation of the model requires some sort of instrumental variable (IV) estimation.

The instruments used are the ratio of year-round, economy wide, employed women to employed men excluding the employed women and men in the Service industry $(L^f_{-s,t} / L^m_{-s,t})$, the 3-month T-bill rates (i_t), and $1/t$, the exogenous variable that captures the effect of non-neutral technological change. The ratio of year-round, economy wide, employed women to employed men excluding the employed women and men in the Service industry $(L^f_{-s,t} / L^m_{-s,t})$, is assumed to be correlated with the supply of female and male workers in occupations in each industry, but not directly correlated with the specific wages of female and male workers within any given industry-occupation. Our intent is to capture general social and economic forces that help shape the relative labor supply of women beyond the economic forces at work in any specific industry. The 3-month T-bill rates (i_t) are considered to be correlated with the relative supply of labor and non-labor inputs in occupations in each industry, but not directly correlated with the specific labor input factor price ratios within each industry-occupation. In an equilibrium industry relative input demand and supply model, the exogenously given T-bill rate would impact relative factor supplies. Given our focus on gender wage gaps, it is important to make sure we have a good identifying instrument for the gender input ratios. Let $R_{it} = L^f_{it} / L^m_{it}$, $i = 1, 2, 3, 4$ and $R_t = L^f_{-s,t} / L^m_{-s,t}$ (economy-wide excluding the Service industry). Note for example that

$$\ln\left(\frac{L^m_{1t}}{L^m_{2t}}\right) = \ln\left(\frac{R_{2t}}{R_{1t}}\right) + \ln\left(\frac{L^f_{1t}}{L^f_{2t}}\right).$$

8. More flexible modeling approaches that relax the assumption of a constant elasticity of substitution across all factors have been considered. For example, we considered a constant elasticity of substitution production function that allows for the elasticity of substitution to be the same among pairs of labor inputs, but different between a composite labor input and the non-labor input:

$$Q = A_t\left[\alpha_t L^\rho + [1-\alpha_t] K^\rho\right]^{\frac{\phi}{\rho}},$$

$L = \sum_{j=1}^{8} \delta_{jt} L_j^\beta$, where L is a composite labor input disaggregated by gender and occupations.

However, the estimating equations from this production function turned out to be intractable.

Our first-stage results for the gender input ratios corresponding to occupations 1 and 2 are given by

$$\widehat{\ln(R_{1t})} = \gamma_{10} + \gamma_{11}\ln(R_t) + \gamma_{12}\left(\frac{1}{t}\right) + \gamma_{13}i_t$$
$$\widehat{\ln(R_{2t})} = \gamma_{20} + \hat{\gamma}_{21}\ln(R_t) + \hat{\gamma}_{22}\left(\frac{1}{t}\right) + \hat{\gamma}_{23}i_t.$$

When we instrument for $\ln(L_{1t}^m / L_{2t}^m)$, we are in effect regressing $\ln(R_{2t}/R_{1t}) + \ln(L_{1t}^f / L_{2t}^f)$ on the instruments to obtain

$$\left(\widehat{\ln\left(\frac{R_{2t}}{R_{1t}}\right) + \ln\left(\frac{L_{1t}^f}{L_{2t}^f}\right)}\right) = \ln\widehat{\left(\frac{L_{1t}^m}{L_{2t}^m}\right)}$$
$$= \hat{\gamma}_{m12,0} + \hat{\gamma}_{m12,1}\ln(R_t) + \hat{\gamma}_{m12,2}\left(\frac{1}{t}\right) + \hat{\gamma}_{m12,3}i_t$$

Similarly, $\ln(L_{1t}^f / K_t) = \ln(R_{1t}) + \ln(L_{1t}^m / K_t)$ so this term is regressed on $\ln(R_t)$, $(1/t)$, and i_t, etc. As discussed in the sub-section below, we are estimating jointly $\binom{9}{2} = 36$ of these "reduced form" equations. By the property of least squares, direct estimates of any log input pairs are simply linear combinations of the estimated parameters of other log input pairs because exactly the same instruments appear in each equation. An alternative might be to use different sets of instruments for each of the 36 log input pairs. Along with a potentially large number of instruments, there would the challenge to ensure internal consistency so that the fitted values for any given log input pair would be invariant to which linear combinations of input pairs are used to obtain a particular pair.

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 justifies the use of instrumental variable methods for all equations. A Sargan overidentification test 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 for a little over 90 percent of the equations. The partial-R^2 and the first stage F-statistic for the excluded instruments pass the significance test for nearly 79 percent of the equations (first stage results are not reported).

Cross-equations restrictions contribute to identification of the model. The cross-equations restrictions comprise restrictions on the elasticity of substitution via the relation $\rho = (\sigma - 1)/\sigma$, as well as additional constraints arising from the internal logic of the model. To understand the need for such additional constraints it is useful to examine the normalization and identification issues that accompany the estimation of the inverse relative demand equations (described in the subsection below).

IV.2 *Normalization and Additional Constraints*

With the inverse demand equation model, one needs $n - 1$ equations to be able to span the entire system of equations with n factor inputs. The normalization used to derive equations (9) and (10), for example, is relative to the labor input h. However, the model can be specified as relative to any of the factor inputs. It is straightforward to back out the relationships associated with any set of wage gaps from the estimated model. Unfortunately, the estimated parameters would not be invariant with respect to the normalization.

Avoidance of the "overidentification" problem necessitates estimating $\binom{9}{2} = 36$ equations for all possible factor price ratio pairings with cross-equation restrictions that uniquely identify the estimated parameters. Note that the residual variance/covariance matrix will be singular because the error terms will be perfect linear combinations of one another. Thus, Three Stage Least Squares estimation cannot be performed for the system of 36 demand equations. Instead we employ Two Stage Least Squares (2SLS) to estimate the system of 36 equations jointly, with appropriate cross-equation restrictions. Because any 8 equations can span the remaining 28 equations, internal consistency requires that additional cross-equation restrictions be imposed on the constant term and the coefficient of the time variable when we jointly estimate all 36 equations. These constraints insure invariance of the estimated coefficients to the choice of any 8 equations. Thus, identification comes down to estimating ρ (the common coefficient on all 36 endogenous log input ratios) 8 unique α_{j0}/α_{h0} parameters and 8 unique α_{j1}/α_{h1} parameters across equations (9) and (10). Specifically, the way the estimation is implemented involves cross-equations restrictions on the α_j and α_h parameters in 28 estimating equations of the type (9) and 8 estimating equations of the type (10). The cross-equations restrictions on the constant and technological change terms are listed below equations (9) and (10). When we adjust for unexplained gender wage gaps, the estimation involves cross-equations restrictions on the α_j^f , α_h^f α_h^m and α_h^m parameters in 16 estimating equations of the type (12), 6 estimating equations of the type (13), 4 estimating equations of the type (14), 6 estimating equations of the type (15) and 4 estimating equations of the type (16). The relations for the cross equation restrictions are listed below equations (12), (13), (14), (15), and (16), respectively.

To demonstrate how the cross-equations restrictions follow from the internal logic of the model, let's take an example. Note that

$$\ln\left(\frac{MP_{2t}^f}{MP_{2t}^m}\right) = \ln\left(\frac{MP_{2t}^f}{MP_{1t}^m}\right) + \ln\left(\frac{MP_{1t}^m}{MP_{2t}^m}\right).$$

The estimates of equation of type (female-male) below

$$\ln\left(\frac{MP_{2t}^f}{MP_{2t}^m}\right) = \beta_{220}^{fm} + \frac{\beta_{221}^{fm}}{t} + (\rho - 1)\ln(\frac{L_{2t}^f}{L_{2t}^m}) + \epsilon_{22t}^{fm}$$

$$\ln\left(\frac{MP_{2t}^f}{MP_{1t}^m}\right) = \beta_{210}^{fm} + \frac{\beta_{211}^{fm}}{t} + (\rho - 1)\ln(\frac{L_{2t}^f}{L_{1t}^m}) + \epsilon_{21t}^{fm}$$

$$\ln\left(\frac{MP_{1t}^m}{MP_{2t}^m}\right) = \beta_{120}^{mm} + \frac{\beta_{121}^{mm}}{t} + (\rho - 1)\ln(\frac{L_{1t}^m}{L_{2t}^m}) + \epsilon_{12t}^{mm}$$

are identified with cross-equation constraints $\beta_{220}^{fm} = \beta_{210}^{fm} - \beta_{120}^{mm}$ and $\beta_{221}^{fm} = \beta_{211}^{fm} - \beta_{121}^{mm}$, where $\beta_{220}^{fm} = \alpha_{20}^{f} - \alpha_{20}^{m}$, $\beta_{210}^{fm} = \alpha_{20}^{f} - \alpha_{10}^{m}$, $\beta_{120}^{mm} = \alpha_{10}^{m} - \alpha_{20}^{m}$, while $\beta_{221}^{fm} = \alpha_{21}^{f} - \alpha_{21}^{m}$, $\beta_{211}^{fm} = \alpha_{21}^{f} - \alpha_{11}^{m}$, $\beta_{121}^{mm} = \alpha_{11}^{m} - \alpha_{21}^{m}$.

V. Results

V.*1* *Results for the Estimations of the CES Production Function with Non-neutral Technological Change*

Before discussing the results note that the impact of non-neutral technological change on relative wages is captured by the coefficient on $1/t$ in the estimating equation (10). Similarly, the effect of non-neutral technological change on relative marginal products is captured by the coefficient on $1/t$ in the estimating equations (12), (13), (14), (15) and (16). A statistically significant negative (positive) coefficient for $1/t$ shows evidence of a narrowing (widening) effect of non-neutral technological change on the gender wage gap over the period of time covered in the sample: 1979-2001. Given the functional form of the CES production function used in this study, $\rho - 1$ is expected to be negative and statistically significant due to the link to the elasticity of factor substitution, $\rho = (\sigma - 1)/\sigma$. Estimated coefficients are obtained for all possible pairings of relative factor price ratios. However, we present only the results for the within-occupation gender wage gaps for economy of presentation and because the focus of this study is on the effect of technological change on the relative wages of female workers within four distinct occupations in the US service industry.

TABLE IV. — The Relation between Technological Change and the Gender Wage Gaps in the US Service Industry: Two Stage Least Squares Estimates of Inverse Relative Input Demand Functions

Independent Variables	Dependent Variables: Relative Wages of Female and Male Workers, by Occupation							
	$\ln(W_1^f/W_1^m)$		$\ln(W_2^f/W_2^m)$		$\ln(W_3^f/W_3^m)$		$\ln(W_4^f/W_4^m)$	
Constant	–.620***	(.021)	.137***	(.021)	–1.243*	(.042)	–.757***	(.026)
$\frac{1}{t}$	–.942***	(.107)	–.209*	(.107)	.313*	(.192)	–.154***	(.056)
$\ln(L_j^f/L_j^m)$	–.349***	(.013)	–.349***	(.013)	–.349***	(.013)	–.349***	(.013)
$\sigma = 1/(1-\rho)$	2.87							
No: of Observations = 87								

Note: Standard errors are in parentheses. * Statistically significant at .10, level; ** at the .05 level; *** at the .01 level (two tailed t-tests).

TABLE IV presents estimates of the effect of technological change on the gender wage gaps in the US service industry without taking into account any potential unexplained gender wage gap (potential discrimination). The results show evidence of the effect of non-neutral technological change on gender wage gaps. The coefficient on $1/t$ is negative and statistically significant for occupations 1 (managerial and professional), occupation 2 (technical, sales, administrative support) and occupation 4 (operators, laborers). This indicates that technological change is associated with a narrowing of the gender wage gap in those three occupations, with the strongest effect on occupation 1 (managerial and professional occupations) where the magnitude of the coefficient is the largest. The coefficient on $1/t$ is positive and statistically significant for occupation 3 (service occupations, precision, craft and repair), suggesting that technological change is associated with a widening of the gender wage gap in occupation 3.

TABLE V. — The Relation between Technological Change and the Gender Wage Gaps in the U.S. Service Industry: Two Stage Least Squares Estimates of Inverse Relative Input Demand Functions taking into Account the Unexplained Gender Wage Gaps

Independent Variables	Dependent Variables: Relative Marginal Products of Female and Male Workers, by Occupation							
	$\ln(MP_1^f / MP_1^m)$		$\ln(MP_2^f / MP_2^m)$		$\ln(MP_3^f / MP_3^m)$		$\ln(MP_4^f / MP_4^m)$	
Constant	–.398***	(.017)	.392***	(.018)	–.909***	(.033)	–.428***	(.022)
$\frac{1}{t}$	–.415***	(.086)	–.038	(.090)	–.039	(.117)	.052	(.050)
$\ln(L_j^f / L_j^m)$	–.323***	(.018)	–.323***	(.018)	–.323***	(.018)	–.323***	(.018)
$\sigma = 1/(1-\rho)$	3.10							
No: of Observations = 89								

Note: Standard errors are in parentheses. * Statistically significant at .10, level; ** at the .05 level; *** at the .01 level (two tailed t-tests).

In contrast to the results presented above, the results presented in TABLE V come from 2SLS estimation of the inverse relative demand functions of type (12), (13), (14), (15) and (16) that adjust for unexplained gender wage gaps. With correction for movements in the unexplained gender wage gap, the dependent variable is the log of relative marginal productivities (observed gender wage ratios plus the estimated unexplained wage gaps from equation (19)) rather than the log of observed gender wage ratios.[9] These results are quite different relative to those presented in TABLE IV. Non-neutral technological change exhibits a statistically significant narrowing effect on the gender wage gap for occupation 1. However, for the other three occupations the coefficient on $1/t$ is not statistically significant, suggesting no effect of technological innovation on the gender wage gaps in those occupations. These results highlight the importance of considering the unexplained gender wage gaps in examining the effect of technological change on the gender wage gaps. They also suggest that the narrowing of the gender wage gaps in occupations 1, 2 and 4 has been mainly driven by changes in the unexplained gender wage gaps (changes in employer based discrimination, etc.), occupation 1 being the only skill level at which technological change had a statistically significant contribution to the narrowing of the wage differentials. The estimates of the quarterly unexplained

9. The number of observations reported in TABLE IV may be different than the largest number of observations possible, 92. For some gender-occupation cells, when estimating the unexplained gender wage differences given by equation (19), micro data on individual characterisitcs X_{jtl}^m and X_{jtl}^f might be missing, resulting in a smaller number of observations.

gender wage gaps in each of the four occupations, obtained from equation (19), show that in occupation 1 the gender wage gap decreased until 1984, and then increased after 1984. The quarterly unexplained gender wage gaps have decreased over time in occupations 2 and 4, while in occupation 3, they did not change.

The magnitudes of the estimated values of the elasticity of substitution among inputs, σ, presented in TABLES IV and V are somewhat larger than the values usually reported in the production function estimation literature. This is explained by the fact that, given the CES production function considered in this paper, the parameter σ does not vary across input pairings. Thus, as different types of labor inputs may be close substitutes, the estimated values for σ would be expected to be higher than those found in other studies.

V.2 *Robustness Checks: Using Direct Measures of Technological Change*

We conduct robustness checks by using direct measures of technological change. The direct measurement of technological change is a problem inherent in all empirical work in this field. Among the available measures for technological change, annual research and development spending (R&D) is the most commonly used in the literature.[10] Annual total R&D expenditure data come from the National Science Foundation. The summary statistics for R&D are shown in TABLE III. When we use $1/RD_t$ in lieu of $1/t$, the results are qualitatively similar to those reported in TABLE IV. Specifically, TABLE VI presents the results of the 2SLS estimations of the inverse relative input demand functions using R&D as a direct measure of technological change and without controlling for unexplained gender wage gaps. The results show evidence of a narrowing effect of technological change on relative wages in occupations 1 and 2, and no effects on the relative wages in occupations 3 and 4. The estimate of the elasticity of substitution among inputs, σ, is significantly smaller compared to when $1/t$ is used.

TABLE VI. — The Relation between Technological Change and the Gender Wage Gaps in the U.S. Service Industry: Two Stage Least Squares Estimates of Inverse Relative Input Demand Functions using R&D as Direct Measure of Technological Change

Independent	Dependent Variables: Relative Wages of Female and Male Workers, by Occupation							
Variables	$\ln(W_1^f/W_1^m)$		$\ln(W_2^f/W_2^m)$		$\ln(W_3^f/W_3^m)$		$\ln(W_4^f/W_4^m)$	
Constant	−.153***	(.056)	.812***	(.078)	−1.15***	(.132)	−1.022***	(.069)
$\frac{1}{RD}$	−2.234***	(.198)	−1.546***	(.174)	−.398	(.335)	−.181	(.091)
$\ln(L_j^f/L_j^m)$	−.516***	(.035)	−.516***	(.035)	−.516***	(.035)	−.516***	(.035)
$\sigma = 1/(1-\rho)$	1.94							
No: of Observations = 87								

Note: Standard errors are in parentheses. * Statistically significant at .10, level; **at the .05 level; *** at the .01 level (two tailed t-tests).

10. Other measures have been considered, such as annual R&D employment, R&D intensity and annual Patent Counts/annual R&D, for each industry. However, R&D and the R&D growth rate are chosen because of availability of consistent data for the years considered in this study.

TABLE VII. — The Relation between Technological Change and the Gender Wage Gaps in the U.S. Service Industry: Two Stage Least Squares Estimates of Inverse Relative Input Demand Functions taking into Account the Unexplained Gender Wage Gaps and using R&D as Direct Measure of Technological Change

Independent Variables	Dependent Variables: Relative Marginal Products of Female and Male Workers, by Occupation							
	$\ln(MP_1^f / MP_1^m)$		$\ln(MP_2^f / MP_2^m)$		$\ln(MP_3^f / MP_3^m)$		$\ln(MP_4^f / MP_4^m)$	
Constant	–.026	(.038)	.731***	(.066)	–1.018***	(.094)	–.714***	(.059)
$\frac{1}{RD}$	–1.510***	(.152)	–.797***	(.140)	–.271	(.197)	.460***	(.067)
$\ln(L_j^f / L_j^m)$	–.398***	(.031)	–.398***	(.031)	–.398***	(.031)	–.398***	(.031)
$\sigma = 1/(1-\rho)$	2.51							
No: of Observations = 89								

Note: Standard errors are in parentheses. * Statistically significant at .10, level; ** at the .05 level; *** at the .01 level (two tailed t-tests).

When the unexplained gender wage gaps are accounted for, the dependent variable becomes the log of relative marginal productivities. The results of the 2SLS estimates taking into account the unexplained gender wage gaps and using R&D as a direct measure of technological change are reported in TABLE VII. The estimates show a narrowing effect on the relative marginal products for occupations 1 and 2, and a widening effect for occupation 4, with no effect on the relative marginal products for occupation 3. Comparing the magnitude of the coefficients in TABLE VII with those reported in TABLE VI, we find evidence of the importance of adjusting for the unexplained gender wage gaps. The magnitudes of the coefficients on $1/RD_t$ reported in TABLE VII are smaller for occupatons 1,2, and 3 and larger for occupation 4 than the magnitudes of the coefficients presented in TABLE VI. This emphasizes the fact that technological change did have an effect on the narrowing of the gender wage gap in occupations 1 and 2, yet one cannot attribute the entire effect presented in TABLE VI to technological change only. The evidence presented in TABLE VII shows that changes in the unexplained gender wage gaps also contributed to a narrowing of the relative wages in occupations 1 and 2 in the US service industry. Additionally, the results show that technological change has a widening effect of the gender wage gaps in occupation 4, once the unexplained gender wage differentials are taken into account.

Results using the R&D growth rate and the R&D ratio are very similar with those using R&D. Other measures that have been considered in the literature are annual R&D employment and annual Patent Counts/R&D. However, data on those variables are not available at industry level.

VI. Concluding Remarks

Our goal in this study has been to investigate the effect of technological change on the narrowing of the gender wage gap in the US service industry the 1980's and 1990's. Taking the approach of a constant elasticity of substitution production function with male and female labor inputs, a non-labor input, and a productivity parameter function that captures non-neutral technological change, we conducted our investigation by level of skill (occupation) using quarterly CPS data on wages and employment for the period 1979-2001.

Our first major finding consists of evidence that non-neutral technological change does have an effect on changes of the gender wage gap; however, the effects vary across levels of skill. Specifically, the results show a narrowing effect of technological change on the female-male wages for the highest skill level occupation (managerial, professional occupations), an effect that is robust to controlling for the unexplained gender wage gap and to using direct measures of technological change in the empirical estimations. However, for the other three occupations, the effect of technological change on the gender wage gaps sometimes diminishes or even disappears once changes in unexplained gender wage gaps are adjusted for. This highlights our second major finding underlying the importance of considering the unexplained gender wage gaps in examining the effect of technological change on the gender wage gaps. The results presented in this study suggest that the narrowing of the gender wage gaps in occupations 1, 2 and 4 has been mainly driven by changes in the unexplained gender wage gaps (reductions in employer based discrimination, etc.) and not by non-neutral technological change. What caused the changes in the unexplained portion of the gender wage gap to evolve differently over time for the skill/occupational categories used in this study? Our model follows common practice in which the coefficient on the pure time trend reflects technological change after conditioning on input ratios and unobserved demand shocks. This type of production model allows only for inputs and random shocks to influence output. Of course, we cannot rule out that external constraints and industrial policies could coincide with pure trend effects. Therefore, it is possible that what we have identified as non-neutral technological change may reflect other factors that have non-neutral effects on gender wage gaps. This paper offers a conceptual framework within which to identify movements in gender wage gaps that are driven by technology related demand factors.

The findings of this study contribute to a better understanding of the effect of non-neutral technological change on changes of wages of female and male workers within major occupations in the service industry, the largest component of the US economy. The results reported here also open avenues for future work in several ways. One continuation of this research is to apply the method proposed here to extend the investigation of the effect of non-neutral technological change on the gender wage gaps to other industries, possibly at a finer skill category level. Another future research avenue is to investigate the use of alternative production technologies that allow for more flexibility in modelling and estimation. The results of this study can lead to an examination of the exact nature of the non-neutral technological change that affects differently each input and skill category. This paper also opens the door to considering other factors contributing to the changes in the gender wage gap, beyond technological change and the unexplained gender wage gaps.

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