THE US GENDER PAY GAP IN THE 1990S: SLOWING CONVERGENCE

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by Francine D. Blau and Lawrence M. Kahn

Abstract

We use data from the Michigan Panel Study of Income Dynamics (PSID) to study the slowdown in the convergence of female and male wages in the 1990s compared to the 1980s. After decades of near constancy, between 1979 and 1989, the female/male hourly pay ratio rose by 17.8 percent—from 63.2 to 74.5 percent. However, convergence slowed in the 1990s, with the ratio increasing to 79.7 in 1998, an increase of 7.2 percent on a ten-year basis. We found that changes in human capital did not contribute to the trends, since women improved their relative human capital to a comparable extent in the 1980s and the 1990s. Occupational upgrading of women and deunionization explained a portion of the slower 1990s convergence since the positive effect of these factors on women's relative wage gains was larger in the 1980s. However, the largest factor accounting for the slowing of wage convergence was the trend in the "unexplained gap," which was sufficient to more than fully account for the slowdown in wage convergence in the 1990s. Controlling for human capital, sector, and the prices of measured and unmeasured labor market skills, women made much larger gains in relative wages in the 1980s than in the 1990s. Factors that may have contributed to the slower narrowing of the unexplained gender pay gap include changes in labor force selectivity, changes in gender differences in unmeasured characteristics and labor market discrimination, and changes in the favorableness of supply and demand shifts. We find some evidence consistent with each of these factors suggesting that each may have played a role in explaining the observed trends.

I. Introduction

After thirty years of relative constancy, the gender pay gap in the United States narrowed substantially in the 1980s. For example, published tabulations from the Census Bureau on the median annual earnings of year-round, full-time workers indicate that the female-to-male ratio rose from 59.7 to 68.7 percent between 1979 and 1989—a gain of 9.0 percentage points. However, the rate of convergence slowed markedly in the following decade, with a further increase to 72.2 percent by 1999—an increase of only 3.5 percentage points. Specific estimates of female relative earnings growth over the two periods differ depending on earnings measures and end points, but the picture of slowing convergence in the 1990s is robust and has been noted by a number of observers (e.g., Blau and Kahn 2000; Fortin and Lemieux 2000; and Welch 2000).[1]

A useful starting point for analyzing the slowdown in women's relative wage gains in the 1990s is to consider what is known about the sources of female gains in the 1980s. In earlier work (Blau and Kahn 1997), we suggested that the 1980s gains were surprising in that they occurred during a period of rising wage inequality in which less skilled workers of both sexes were faring poorly. To the extent that this trend reflected rising returns to skills and to employment in high-wage sectors, it could be expected to disadvantage women as a group relative to men. We presented evidence that women were able to successfully "swim upstream" against the current of rising inequality due to a number of factors which offset its adverse effects: women narrowed the gender gap in skills, particularly their labor market experience (see also O'Neill and Polachek 1993), and upgraded their occupations; deunionization reduced the gender pay gap because men lost union jobs at a faster rate than women; and women also benefited from a substantial narrowing of the "unexplained" pay gap, which may reflect a reduction in labor market discrimination, an improvement in women's unmeasured characteristics, or more

[1] Blau and Kahn (2000) report similar trends for the gender earnings ratio based on hourly earnings of full-time workers computed from the CPS; they find it increased from 65.5% in 1978 to 74.1% in 1988 and 78.2% in 1998.

favorable demand and supply shifts for women compared to men. The latter may result if factors affecting the wage structure, such as technological change, proceeded in ways that favored women relative to men.

Based on these findings, one may identify a number of possible sources for the slower progress of women in the 1990s—each of which could potentially play role. First, relative improvements in women's measured characteristics may have proceeded at a slower pace in the 1990s than in the 1980s. Blau and Kahn (2000) note in particular the possibility that women enhanced their average experience levels at a slower pace in the 1990s. This is plausible in that increases in female labor force participation rates were much slower in the 1990s than in the 1980s (Blau, Ferber and Winkler 2002, Ch. 4), although it is not possible to directly infer trends in women's average experience levels from trends in their participations rates (e.g., Goldin 1990).[2] The impact of trends in the gender gap in experience as well as of other measured characteristics will be a primary focus of our investigation of the 1990s trends.

Another possibility is that discrimination narrowed at a slower pace in the 1990s. Views on this are mixed. On the one hand, the General Accounting Office (GAO) issued a report in 2001 based on Current Population Survey (CPS) data that found that the gender salary gap among full-time managers actually increased in the majority of industries surveyed between 1995 and 2000 (GAO 2001, p. 19). These findings have provoked renewed concerns about "glass ceilings," as exemplified by a 2002 report by Representatives John D. Dingell and Carolyn B. Maloney (Offices of John D. Dingell and Carolyn B. Maloney, 2002). On the other hand, O'Neill (2003) argues that, at least within occupations, we have largely achieved pay parity between men and women, implying that the slowing in convergence was inevitable. For example, she reports that in the National Longitudinal Survey of Youth (NLSY) sample in 2000, aged 35-43 at that time, the female/male hourly pay ratio adjusted for schooling, ability, experience and occupational characteristics was 97.5% (the raw pay ratio was 78.2%). O'Neill

[2] This is because increases in female labor participation can be due to increased entry or increased labor force attachment of women, or a combination of both.

concludes that, although gender role differences continue to cause a gender pay gap, discrimination against women is largely a thing of the past.[3]

Other explanations center around the possibility that demand- and supply-side shifts played out differently in the 1980s and 1990s resulting in a larger decrease in the gender pay gap as well as a larger increase in male inequality in the 1980s than in the 1990s. Welch (2000), for example, points to a rising relative demand for intellectual skills relative to physical strength, due to technological advances, which benefited women as a group relative to men and high-skilled compared to low-skilled men. In this view, the slowing increase in male inequality that occurred in the 1990s (e.g., Katz and Autor 1999) is consistent with a tapering off of these demand shifts and thus of slower relative progress of women. Note that this perspective leads one to expect an inverse relationship between trends in male wage inequality and trends in the gender pay gap. Such an inverse relationship is also expected based on Fortin and Lemieux's (2000) analysis, which posits that women's gains result in men's losses as, for example, women enhance their skills and move up the job hierarchy, displacing men as they do so.

In this paper, we shed light on each of these possible sources of slowing convergence in the 1990s using data from the Michigan Panel Study of Income Dynamics (PSID), the only nationally representative data base that contains information on workers' actual labor market experience. Ours is the first study to provide a detailed examination of this issue employing micro-level data and including information on experience, which has been shown to be an extremely important factor in explaining the gender pay gap (Mincer and Polachek 1974) and, as we have seen, its trends.

Data on wages are available only for a self-selected group of labor force participants. The resulting selection bias (Heckman 1979) is of particular concern if, as we have seen, women's labor force participation grew more rapidly in one period (the 1980s) than in the other (the 1990s). The direction of any bias is unclear, a priori. An obvious scenario is that, as

[3] Of course, if occupational representation reflects employer hiring decisions, then controlling for occupation may lead to us to underestimate the full extent of discrimination against women.

women's employment rises relative to men's, women included in the sample of wage earners may become less positively selected as those with lower potential wage offers are drawn in. If this is the case, comparisons of observed relative wages over time may underestimate the convergence in wage offers. However, an individual may also be out of the labor force because he or she has an especially high value of home time, a possibility that is particularly credible for women. Regardless of whether the growth in female employment is positively or negatively selected, it is important to take account of selection in assessing the wage offers of women relative to men. The longitudinal nature of the PSID allows us to implement recently devised adjustments for sample-selection bias (Neal 2004).

II. Trends in the Gender Pay Gap: Overall Patterns

Table 1 contains information on male and female real wages for 1979, 1989 and 1998, based on the PSID. (Additional details regarding the data are presented below.) Since our two time periods are of unequal length (i.e., ten and nine years, respectively), for comparability, here and elsewhere in the paper, changes over each period are expressed as the average annual change (uncompounded) multiplied by ten. Mirroring the trends we discussed above based on published data, we find that the pay gap fell substantially faster in the 1980s than in the 1990s: the gender differential in log wages fell 0.164 log points from 1979 to 1989 compared to a ten year rate of decline of .075 log points from 1989 to 1998. The implied female-to-male pay ratio rose from 63 percent in 1979 to 74 percent in 1989 and 80 percent in 1998. The data in the table also reflect well-known trends in real wage growth, with men's real wages declining or stagnating and women's real wages growing at 10 to 11 percent over the two periods.[4] Wage inequality as measured by the standard deviation of log wages or the 90-10 gap in log wages rose in each decade for both men and women, with larger increases in the 1980s than in the 1990s. The

[4] These are approximations based on the log wage differences.

slowing increase in wage inequality in the 1990s has been noted by several authors (e.g., Katz and Autor 1999).

Figure 1, which displays the gender pay gap at the indicated percentiles of the male and female wage distributions, shows that the gender pay gap fell substantially throughout the wage distribution in the 1980s, with much smaller declines throughout the distribution in the 1990s. The figure also indicates little wage convergence at the top of the distribution in the 1990s, a finding consistent with the concerns raised by the GAO report cited above. We will examine this issue below controlling for gender differences in measured characteristics by using quantile regression techniques.

Rising skill prices may induce changes in the gender pay gap that are unrelated to women's relative qualifications or to the extent of discrimination against them. A simple measure which controls for such changes in wage structure is the mean female percentile in the male wage distribution, although such a measure does face some criticisms that are considered below. The female percentiles presented in Table 1 indicate that the behavior of this indicator was similar to the gender pay ratio: women moved up in the male pay distribution in both periods, but the pace of this upward progression was slower in the 1990s than in the 1980s. On average, woman outearned 24% of men in 1979, 35% in 1989, and 39% in 1998.

III. Decomposing the Changes in the Gender Wage Gap

A. Analytical Framework

Using a decomposition suggested by Juhn, Murphy and Pierce (1991)—JMP—and implemented to analyze trends in the U.S. gender pay gap in the 1980s by Blau and Kahn (1997), we identify, in an accounting sense, the contribution to changes over time in the gender pay gap of i) changes in the measured characteristics of women compared to men, ii) changes in the prices of measured characteristics; and iii) changes in the unexplained gap (corrected for the impact of changes in the prices of unmeasured characteristics).[5] The portions of the JMP decomposition dealing with the quantities and prices of measured characteristics are fairly noncontroversial, while there has been more disagreement about the decomposition of the residual. We first explain the decomposition and then consider criticisms and qualifications.

The basic insight of the JMP framework is that, since prices change over time in ways that may advantage or disadvantage women, it is useful to separately identify the impact of gender-specific factors like relative qualifications of women and discrimination against them from the effect of wage structure (or price changes that are common to both sexes). Intuitively, if, as the human capital model suggests, women have less experience than men, on average, the higher the return to experience, all else equal, the higher will be the gender gap in pay. Similarly, if, due to discrimination or other factors, women tend to work in different occupations and industries than men, the higher the return to working in the male sector, the larger will be the gender pay gap. This reasoning suggests that rising wage inequality due to increasing returns to skill and sector would adversely affect women's relative pay.

On the other hand, a rising relative demand for intellectual skills relative to physical strength (Welch 2000), or for white collar relative to blue collar workers (Berman, Bound and Griliches 1994) due to technological advances, may benefit women as a group relative to men but also increase male wage inequality (see also, Blau and Kahn 1997). Following this reasoning, rising wage inequality might be expected to have opposing negative and positive effects on women's relative wages, with the dominant effect being an empirical question. The negative effects are captured in the components of the JMP decomposition that measure the impact of changes in measured and unmeasured prices on changes in the gender pay gap. The impact of technological change and other factors that potentially positively affect the relative

[5] This framework or a simpler correction for a group's position in the wage distribution has been used to study trends over time or international differences in the labor market outcomes of blacks, women and immigrants (e.g., Juhn, Murphy and Pierce 1991; LaLonde and Topel 1992; Blau and Kahn 1992, 1996, and 1997; Borjas 1995; Datta Gupta, Oaxaca and Smith 2003; and Welch 2003).

demand for female workers will be included in the effect of changes in the unexplained portion of the gender pay gap.

Institutional changes are an additional factor that can affect the return to skill but may have gender-specific effects as well. For example, deunionization likely raises wage inequality and the price of skills, since unions compress wages (DiNardo, Fortin and Lemieux 1996). One might therefore expect that deunionization would raise the gender pay gap by making wage floors less prevalent. But in the 1980s, the unionization rate fell more for men than for women, actually helping to explain the falling gender pay gap (Blau and Kahn 1997). We can directly assess the latter impact of deunionization more easily than technological change, since we can observe it directly. However, any more general effects of deunionization through spill-over or threat effects on the nonunion sector, will not be measured by our analysis.[6]

Using the JMP framework, we begin with a male wage equation:

(1) $$Y_{it} = X_{it}B_t + \sigma_t\theta_{it},$$

where Y_{it} is the log of wages; X_{it} is a vector of explanatory variables; B_t is a vector of coefficients; θ_{it} is a standardized residual (i.e. with mean zero and variance 1 for each year); and σ_t is the residual standard deviation of male wages for that year (i.e., its level of male residual wage inequality). The difference in the gender pay gap between two years 0 and 1 (i.e., 1979-89 and 1989-98) can be decomposed into four components as follows (for additional details see Appendix A and Juhn, Muphy and Pierce 1991):

(2) $$\text{Observed X's Effect} = (\Delta X_1-\Delta X_0)B_1$$

(3) $$\text{Observed Prices Effect} = \Delta X_0(B_1-B_0)$$

[6] Given the relatively small size of the union sector in the United States, such effects are not likely to be large empirically, and indeed a recent study does not find much evidence of them (Farber 2003). Note, however, the evidence suggests that the union impact on the nonunion sector in many other OECD countries is substantial and hence that international differences in the extent of unionism have a substantial effect on the overall wage distribution and on the relative wages of women (e.g., Blau and Kahn 1996).

(4) Gap Effect = $(\Delta\theta_1-\Delta\theta_0)\sigma_1$

(5) Unobserved Prices Effect $=\Delta\theta_0(\sigma_1-\sigma_0)$

where a Δ prefix signifies the average male-female difference for the variable immediately following.

The Observed X's Effect reflects the contribution of changing male-female differences in observed labor market qualifications (X). It measures the impact of, e.g., a decrease in the gender gap in experience on the change in the pay gap. The Observed Prices Effect reflects the impact of changes in prices of observed labor market characteristics, as indexed by male prices. For example, given that women have lower actual experience levels, an increase in the return to experience would weight the female experience deficit more heavily and hence raise the gender pay gap, *ceteris paribus*. The Gap Effect measures the effect of changing differences in the relative positions of men and women in the male residual wage distribution. That is, it gives the contribution to the change in the gender gap that would result if the level of residual male wage inequality had remained the same and only the percentile rankings of the female wage residuals had changed. It would, for example, capture the effect of an improvement in women's unmeasured characteristics or a reduction in the extent of discrimination against women. Finally, the Unobserved Prices Effect reflects the impact of differences in residual inequality between the two years. It measures the contribution to the change in the gender gap that would result if the percentile rankings of the female wage residuals had remained the same and only the extent of male residual wage inequality had changed. Suppose, as is likely, that unmeasured deficits in relative skills or discrimination lower women's position in the male distribution of wage residuals. The larger the penalty to being below average in the residual distribution, the larger the gender pay gap will be. The sum of the gap and unobserved prices effects is equal to the change in the "unexplained" differential, which is commonly taken as an estimate of discrimination in a conventional decomposition.

Recently, this decomposition has come under a variety of criticisms, particularly the decomposition of the residual into a portion representing the effect of changes in the treatment or unmeasured characteristics of women and a portion representing the impact of changes in prices. For example, Suen (1997) has argued that labor market discrimination can lead to a spurious, mechanical positive relationship between the female percentile (in the male distribution) and male wage inequality.[7] Specifically, suppose the only source of gender pay differentials is discrimination taking the form of a constant discount on female wages of d log points independent of any skill prices. Then an increase in male wage inequality will mechanically raise the typical woman's percentile in the male wage distribution, and the female percentile will be uninformative about the relative treatment or qualifications of women. On the other hand, if discrimination takes a more complicated form in which the impact of discrimination is affected by changes in the wage structure (Edin and Richardson 2002), then the female percentile in male distribution will be informative about women's treatment. For example, in a model where one's wage is determined by one's position in a job hierarchy, the female percentile could be an indicator of placement in the wage hierarchy.[8] In such a scenario, a rising return to placement in the job hierarchy would raise the observed gender pay gap, even in the absence of any increase in discrimination against women, and changes (or stability) in the average female percentile would be highly informative about women's labor market position.

This discussion suggests that the relevance of Suen's (1997) criticism is an empirical question. There is some indirect evidence in our results and elsewhere that the female percentile in the male distribution is informative about women's treatment or unmeasured skill levels. First, Table 1 shows that women's placement in the male distribution increased both in the 1980s and the 1990s, with a faster increase in the 1980s, mirroring the time pattern in the rise of the

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[7] Juhn, Murphy, and Pierce (1991) and Blau and Kahn (1992, 1996 and 1997) also discussed the possibility that discrimination could complicate the interpretation of the residual.

[8] Of course, women's productivity can also affect their position in the job hierarchy; thus even in this scenario, we would not be able to distinguish discrimination from unmeasured productivity. But we would be able to use the JMP decomposition to disentangle gender-specific factors from wage structure as causes of the changing gender gap.

female/male pay ratio (although it must be acknowledged that the behavior of the female percentile also mirrors the changes in male inequality). Below, we present similar findings for women's percentile ranking in the distribution of wage residuals and the magnitude of unexplained gender pay gap. Second, our results in Table 1 and below indicate that men and women have experienced similar changes in wage inequality (see also, Blau and Kahn 1997; Blau 1998), suggesting that both have been subject to broadly similar forces impacting wage structure.[9]

An additional implicit criticism of the JMP approach is suggested by the Welch (2000) model discussed above in which technological progress raises the return to intellectual skills, lowering the gender pay gap and raising male wage inequality, while in the JMP framework, rising skill prices necessarily hurt those with lower skills. We have noted above that both these alternatives may be captured in the JMP decomposition, with the net effect being an empirical issue. Interestingly, Welch (2000) finds empirically, using time series CPS data, that women's relative wages are negatively correlated with the male 50-10 wage gap (an effect that is nearly significant) but significantly positively correlated with the male 90-50 wage gap. The first finding is consistent with the JMP approach and suggests that the male 50-10 gap may be an indicator of the return to skills such as experience in which women have a deficit, while the second finding is consistent with Welch's model in which rising intellectual skill prices help women.

A final criticism of the JMP method is based on Fortin and Lemieux's (1998; 2000) model discussed above in which rising female relative wages cause rising male wage inequality, as men are displaced in the job hierarchy by women. Their approach does not invalidate the reasoning in which rising prices of measured skills for which women have a deficit or rising returns to working in male sectors raise the gender pay gap. However, their model suggests that

[9] Similarly, across countries, male and female wage inequality are very highly correlated, again suggesting that men and women are both similarly affected by labor market prices (Blau and Kahn 1996). In addition, across countries, there is little relationship between the female percentile and male wage inequality (Blau and Kahn 2000), a piece of evidence not consistent with the existence of a mechanical relationship between the two.

it may be artificial to simulate what would happen to women's wages if they moved up the hierarchy (i.e., their percentile ranking in the male distribution of wage residuals increased) but the male distribution of wage residuals was kept fixed. We therefore use caution in interpreting the JMP residual decomposition.

B. Data and Specifications

Three waves of the PSID are employed to compare the rate of convergence in the 1980s and the 1990s—1980, 1990 and 1999[10]—allowing us to compute average hourly earnings for 1979, 1989 and 1998. In addition to spanning the appropriate time period, the economy was expanding in each of these years, suggesting that overall macroeconomic conditions may have been similar: the unemployment rate was 5.8% in 1979, 5.3% in 1989 and 4.5% in 1998 (BLS web site: www.bls.gov, accessed 6/9/03). We initially restrict our analysis of wages to workers who were, as of the survey date, full-time, nonagricultural employees age 18-65; the self-employed were excluded. To maximize sample size, we use both the PSID's random sample and its poverty oversample populations and in all analyses employ the sampling weights supplied in the PSID files. Patterns were similar when we restricted ourselves to the random sample. The wage measure used is average real hourly earnings during the previous calendar year expressed in 1983 dollars using the Personal Consumption Expenditures deflator from the National Product Accounts. We excluded anyone earning less than $1 or more than $250 per hour in 1983 dollars. The Appendix contains details on the construction of the key experience variables.

The PSID collects detailed work history data only for "heads" of families and "wives" (including cohabitors) rather than for all adult individuals. We therefore also make some comparisons with the March CPS for the same years in order to gauge the representativeness of the PSID. A comparison of the data in Table 1 with tabulations from the March Current Population Survey (CPS) for the same years, shown in Table A1, indicates that trends in the

[10] After the 1997 survey, the PSID began surveying respondents every other year rather than annually. Thus, there are no PSID data available for 2000.

gender pay gap, wage inequality, and female placement in the male wage distribution in the PSID are very similar to those in the CPS.[11] The CPS comparisons give us some confidence in the representativeness of the PSID.[12]

Two specifications are employed in implementing the decomposition. The "human capital" specification includes race, education variables, and experience variables (see Appendix Tables A2 and A3 for variable means and regression results). The race variable is primarily a control. Sample sizes were insufficient to perform separate analyses for nonwhites, although results were very similar when we confined the sample to whites only. Education is measured by three variables including years of schooling and dummies for college degree only and for advanced degree. Experience includes full-time and part-time experience and their respective squares.[13]

The second "full" specification augments the human variables with a collective bargaining coverage indicator and a set of 19 occupation and 25 industry dummy variables that include some two digit and some one digit categories, depending on cell size. Controlling for sector in this way is potentially interesting, since existing research finds that much of the gender gap is associated with location of employment (Blau 1977; Groshen 1991; Bayard, Hellerstein, Neumark and Troske 2003). Further, factors such as deunionization and occupation and industry shifts clearly in part reflect changing demand for labor, and this specification allows us to examine the importance of these factors. We thus present some results controlling for these

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[11] The CPS data refer to average hourly wage and salary earnings for full-time, nonagricultural wage and salary workers age 18-65 in the indicated calendar year. All analyses use CPS March Supplement sampling weights.

[12] The only noticeable difference between the PSID and CPS data is that real wage levels were consistently 9-14% higher in the PSID than the CPS. About 1-2 percentage points of this 9-14% can be explained by differences in the definition of the earnings variable. Specifically, in the CPS, the earnings variable is wage and salary income. In the PSID, this variable is available for heads but not wives. Therefore, for analyses using the PSID, we use total labor earnings for people who report that they were not self employed on their main job. For men and female heads in the PSID, we are able to compute both wage and salary earnings and total labor earnings; total labor earnings are about 1-2% higher than wage and salary earnings. As regards the remaining differences, other researchers have also noted that income or earnings levels tend to be higher in the PSID than in the CPS data (Kim and Stafford 2000; Gouskova and Schoeni undated; and Gottschalk and Moffitt 1992).

[13] In view of the possibility that the returns to education changed differently for different experience groups (Card and Lemieux 2001), we also implemented the JMP decomposition interacting the three education variables with full time experience and its square; the results were unchanged.

variables and have moreover attempted to specify the categories in as detailed a fashion as possible to make the results as informative as possible. However, the sector variables are also potentially endogenous as they themselves are likely to be affected by relative wages through both worker supply and employer demand decisions. Further, access to occupations, industries and unionized workplaces may be affected by employer discrimination. We thus present results for both specifications but interpret the "full" specification cautiously.

We have not controlled for marital status or number of children, although they may be important factors influencing the pay gap. An alternative would have been to include them as productivity characteristics. However, such an approach is problematic since these variables may well proxy higher skills for men (see Korenman and Neumark 1991, for the analysis of marital status), but possibly lower skills for women, even controlling for actual labor market experience (e.g., Waldfogel 1998). The approach we have followed allows us to place a sharper interpretation in the decomposition on the impact of differences in labor market skills.

C. Empirical Results

Tables 2A and B show the results of the JMP decomposition of changes in the gender pay gaps across our two periods: 1979-89 and 1989-98. We first consider the descriptive statistics presented in 2A and then the full decomposition results in 2B. Table 2A shows similar patterns of rising residual inequality for both men and women. While the residual standard deviation rose faster in the 1990s than the 1980s, the residual 90-10 gap increased more rapidly in the 1980s than the 1990s—a pattern similar to that for overall wage inequality (see Table 1).[14] The similar

[14] In the CPS, both the residual 90-10 gap and the residual standard deviation increased more rapidly in the 1980s than the 1990s. The CPS regressions control for potential not actual experience, since information on actual experience is not available in the CPS; and education is measured as years of schooling only, since explicit information on college and advanced degrees is not available in the CPS data except in 1999. The CPS changed its education question in 1994. For the 1999 CPS, we used Jaeger's (1997) suggested mapping of the new education variable into the traditional years of schooling measure. The JMP results using the CPS and the PSID are quite similar when the same potential experience and education specification is employed (see Table A4). Note that the relative educational attainment of women increased somewhat more in the 1980s and somewhat less in the 1990s in the CPS than in the PSID data. Specifically, the changes in the (male minus female) gender gap in mean years of schooling were 0.006 (PSID) and –0.098 (CPS) in the 1980s; and –0.266 (PSID) and –0.080 (CPS) in the 1990s.

trends in residual inequality for men and women give us some confidence that the JMP assumption of a common labor market for men and women may be valid, however, as noted above, supply and demand shifts that affect men and women differently will be captured in the unexplained portion of the differential and provide a possible explanation for changes in the unexplained gender pay gap over time.

In both specifications, the average female residual fell dramatically in the 1980s but was virtually constant over the 1990s. This residual is the conventional measure of labor market discrimination but is generally acknowledged to also include the effects of gender differences in omitted variables. These results indicate that, controlling for the human capital variables, including actual labor market experience, the gender wage ratio increased from 70.8 to 81.9 percent between 1979 and 1989, and remained roughly constant at 81.2 percent in 1998. In the full specification, which adds controls for industry, occupation and collective bargaining coverage, the ratio increased from 81.6 percent in 1979 to 91.0 percent in 1989 and remained at 91 percent in 1998. The mean female percentile in the residual distribution, a measure that, in the context of the JMP framework is independent of possible adverse shifts in the prices of unobservables, followed a similar pattern, rising sharply in the 1980s and only very slightly in the 1990s.

Table 2B show the decompositions of the changes in the gender pay gap over the 1980s and the 1990s. The 1980s decomposition is very similar to our earlier work that which covered the 1979-88 period (Blau and Kahn 1997).[15] Specifically, the human capital specification shows that women improved their relative experience levels in the 1980s, contributing to a 0.0528 log point fall in the gender pay gap, or about 1/3 of the total decline. In addition, women moved up

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These differences in educational trends in the PSID and CPS are reflected in the Observed X's effects shown in the Table A4.

[15] Note that the results for the 1980s presented in this paper differ somewhat from those presented in Blau and Kahn (1997) for two reasons, in addition to the slight difference in time period. First, the earlier study employed only the PSID random sample whereas in the current study, to maximize sample size, we use both the PSID's random sample and its poverty oversample populations (and employ the appropriate sampling weights). Second, taking advantage of the larger sample size we specify a more detailed set of industry and occupation controls in the current study.

the male residual distribution, an effect contributing to a 0.1801 log point decrease in the gender pay gap, or more than the actual decline. However, both measured prices and unmeasured prices changed to women's detriment and served to increase the gender pay gap by 0.0651 log points. The full specification for the 1980s yields a larger observed X effect and a gap effect that is smaller in absolute value, suggesting that more of the observed change in the gender pay gap can be explained with the addition of the occupation, industry and union controls. In addition to the upgrading in female labor market experience, women's occupations improved, and deunionization had a greater negative effect on men's than on women's wages, since men lost union jobs at a faster rate than women. Measured prices served to raise the gender pay gap overall, although occupational price effects were negative.[16]

Comparing the JMP decompositions for the 1980s and the 1990s can reveal some of the sources of the slowdown in the convergence of the gender pay gap. Using either the human capital or the full specification, we find that women upgraded their human capital as measured by education and experience to a similar degree in the two decades. In the 1980s this upgrading consisted entirely of rising experience and, consistent with speculations based on aggregate labor force participation rates, decreases in the gender gap in experience contributed considerably less to wage convergence in the 1990s than in the 1980s. The gender gap in years of full-time experience decreased by .7 years between 1989 and 1998, compared to 2.3 years between 1979 and 1989. However, rising relative educational attainment of women played a much larger role in the 1990s, and thus, the sum of the effects of education and experience was similar in the 1980s and 1990s. Although men had an edge in the incidence of college degrees in earlier years, by 1998 the incidence of college degrees was slightly (1.2 percentage points) higher among women.[17]

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[16] The negative occupational price effect contrasts with our earlier work and is likely due to our ability to more finely define occupation in the larger samples we now use.

[17] Women became 50 percent of those receiving bachelor's degrees in 1981-82 and their representation has increased steadily since then to 57.3 percent in 2000-2001 (see NCES web site: http://nces.ed.gov, accessed 9/17/03). The relative educational attainment of women full-time workers is influenced by these trends, as well as by selection into full-time employment and the retirement of earlier, less well-educated cohorts. As noted above, increases in relative years of schooling completed of women are somewhat larger in the 1980s and somewhat

The full specification shows that, while occupational upgrading and deunionization contributed to women's relative wage gains in both periods, these factors had larger effects in the 1980s than the 1990s, explaining roughly 0.0241 log points of the 0.0890 faster closing of the gender pay gap in the 1980s, or about 27%. Occupational shifts were similar in a number of respects in both periods. Women increased their relative representation in managerial occupations and in professional jobs (both overall and excluding k-12 teaching) and reduced their relative representation in clerical and service jobs at about the same pace in the two decades. However, the gender difference in representation in craft and operator jobs declined more rapidly in the 1980s than the 1990s. This was because men moved out of (or lost) these jobs at a faster rate in the earlier decade. The results for collective bargaining coverage reflect a slowing pace of deunionization for both men and women in the 1990s than in the 1980s, with a smaller gender difference in the rate of deunionization in the 1990s. The larger loss of relatively high-paying blue collar and unionized employment for men in the 1980s than in the 1990s may be indicative of larger demand shifts favoring women in the 1980s.

While more favorable shifts in occupations and collective bargaining coverage for women in the 1980s help to explain some of the faster convergence in that decade, adverse trends in measured and unmeasured prices worked to widen the gender pay gap more in the 1980s than the 1990s. Specifically, trends in measured prices were estimated to slow convergence in the 1980s compared to the 1990s by .0588 (human capital specification) to .0442 (full specification) log points, while trends in unmeasured prices worked to slow convergence in 1980s relative to the 1990s by 0.0121 to 0.0188 log points.

The results in Table 2B indicate that the primary factor accounting for the more rapid convergence in women's wages in the 1980s was the gap effect: unexplained gender differences in wages, corrected for unmeasured price changes using the JMP decomposition, narrowed more

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smaller in the 1990s in the CPS than in the PSID. If education played a more even role across the two decades than suggested by the PSID data, human capital factors taken as a whole (i.e., including the slowing convergence in experience between men and women in the 1990s) might explain more of the slowing convergence in the gender pay gap between in the 1990s. However, note too that the CPS had a major revision of its educational variables between 1990 and 1999, making comparability of the education variables in the two CPS's problematic.

dramatically in both the human capital and full specifications in the 1980s than in the 1990s; and this difference is more than sufficient to fully account for the slowdown in convergence in the 1990s. Women's more rapid movements up the male distribution in the 1980s produced gap effects narrowing the gender gap by 0.1279 to 0.1801 log points, in contrast to the much smaller negative effects of 0.0063 to 0.0074 log points for the 1990s. This contrast means that, controlling for measured human capital and sector, women's relative labor market position improved much more in the 1980s than the 1990s. While it is reassuring to have a measure of changes in the unexplained gap that is corrected for the negative effects on women's wages (in some models) of widening residual male inequality, in fact our conclusions are similar if we restrict ourselves to changes in the conventionally defined unexplained differential also shown in Table 2B.

The slower convergence in the unexplained gap in the 1990s compared to the 1980s has at least three possible, nonmutually exclusive substantive sources: first, gender differences in unmeasured characteristics may have narrowed at a faster pace in the 1980s than in the 1990s; second, reductions in labor market discrimination against women may have proceeded at a faster pace in the 1980s than in the 1990s; and finally, demand and supply conditions for women may have changed more favorably in the 1980s than the 1990s. An additional factor to be considered is the change in labor force selectivity among men and women in each period, which may have contributed to an apparent slowdown in wage convergence overall and/or in the unexplained gender pay gap. In the following section, we consider some evidence that each of these factors may have played a role in the faster 1980s convergence in the relative wages of women. Evidence on the impact of selectivity is considered prior to the assessment of the impact of the other factors since it is important to know whether the differential trends in the unexplained gap persist after adjusting for selection bias.

IV. Factors Contributing to a Slowing Convergence in the Unexplained Gender Pay Gap in the 1990s

A. Changes in Labor Force Selectivity

Our approach to analyzing the impact of labor force selectivity on trends in the raw and unexplained gender wage gap is to get more information on the wages of those not included in our sample of full-time employed workers. An alternative would be to build sample selection models and then predict the wage offers of those without observed wages (Heckman 1979). However, since the identification conditions required for the successful implementation of such techniques are potentially severe, we take the more modest approach of looking harder for evidence on offers. We proceed in several stages, each of which allows us to include a successively larger portion of the adult population in our calculations.

First, we add all of those with observed hourly earnings in the current year to our base sample of full-time workers; that is, we include part-time workers. Second, for those with no earnings in a given year for which we measure wages, we use the longitudinal nature of the PSID to recover a real hourly earnings observation from the most recent year for which one is available, with a maximum window of four years. Third, for those for whom we still have no observation on wages under these procedures, in the spirit of Neal and Johnson's (1996) and Neal's (2004) analyses of black-white wage differentials, we include some additional individuals by making assumptions about whether they placed above or below the median in real wage offers. Specifically, we assume that individuals with at least a college degree and at least eight years of actual full-time labor market experience had above the median wage offer for their gender; and that those with less than a high school degree and less than eight years of actual labor full-time market experience had below median wage offers for their gender. Note that this procedure takes into account that for women it would not be appropriate to assume that all those outside the wage sample have below median wage offers, since some women are outside the wage sample due to a high value of home time rather than a low wage offer. Further, our imputations take into account, in addition to education, actual labor market experience, a crucial variable influencing women's wages.[18] If these wage assumptions are valid, we can use median regression to estimate raw (i.e., unadjusted) and human-capital corrected gender differences in wage offers for the expanded group.[19] Koenker and Bassett (1978) show that under some non-normal distributions, the sample median has a smaller asymptotic variance than the sample mean, suggesting that median regression may well estimate effects of explanatory variables with smaller errors than linear regression.

Table 3 shows the fraction of the population included in our base sample of full-time workers and in our successively more inclusive wage samples.[20] It indicates that our base sample is indeed very selective with respect to women, with only 41% of women in the population included in 1979, rising to 50% in 1989 and 53% in 1998. Moreover, since this group grew very quickly in the 1980s and more slowly in the 1990s, selection may have differentially affected the wage trends during these two periods. In contrast, the inclusion of men in the full-time sample is much greater and fluctuates less over time—including 80 to 83

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[18] Applying these assumptions to individuals who had observed wage offers misclassifies 9-15% of men and 14-21% of women with less than twelve years of school and less than eight years' actual labor market experience and 17-22% of men and 11-20% of women with at least a college degree and at least eight years' actual experience. Thus, while the imputation clearly makes some errors, they may have a low incidence. Results were not sensitive to some alternative education and experience cutoffs for inclusion in these imputed wage samples.

[19] While this assertion is correct for the raw gap, we need stronger assumptions about unobserved wage offers in order to make conclusions about the human capital-corrected pay gap. Specifically, for the individuals without observed wage offers, we need to assume that those with less than a high school degree and less than eight years' full time experience had below median wage offers *conditional on their human capital levels*; by the same token we must assume that those with college degrees and at least eight years' full time experience had above median wage offers conditional on their human capital. A similar point is made by Neal (2004). These assumptions are discussed further below.

[20] Those who were self-employed or agricultural workers as of the time wages were analyzed (1979, 1989 or 1998) are excluded from both the numerator and the denominator for all samples in Table 3. In retrieving past wages for sample (c), we exclude individuals who were agricultural workers at the time their past wage was measured. We did not exclude individuals whose past wage was based on self-employment because, for the 1977 and 1978 samples of wives, we were unable to determine self-employment status. However, in supplementary analyses for 1989 and 1998 (when self-employment status of wives could be determined), we excluded individuals whose past wage was based on self-employment and found virtually identical results to those reported here. Moreover, when we added the self-employed and agricultural workers to all of the samples in Table 3, the findings for the selection corrections were similar to those reported below.

percent of the population over the period. Thus, concerns about selection are centered primarily on women, and results for this group will drive our selection-correction adjustments.

Table 3 shows that we add substantially to the female and male samples when we include all those with earnings in the prior year (i.e., part-time workers): the share of all women with wage observations now ranges from 68 to 77%, while for men, the sample includes 92 to 94% of the population. Recovering past observed wages for those without current observations using a four-year window adds 10 to 13 percentage points to female coverage and 4 to 5 percentage points to male coverage. Finally, making our above and below median imputations for selected individuals without present or recovered past wage observations leads to very high rates of coverage of the population: fully 86-91% of women and 96-98% of men are now covered. Not only is the coverage within a given year much closer for men and women than under less inclusive definitions of the sample, the rise in female coverage for the expanded sample—4.3 percentage points (1979-89) and 0.4 percentage points (1989-98)—is much less than for the full-time employed sample—8.7 percentage points (1979-89) and 2.8 percentage points (1989-98).

Table 4 shows median log wage gaps (Panel A) and the changes in these gaps (Panel B) for the four samples described above. Two estimates for each year are presented. The first is the raw (unadjusted) gap and the second is the gap controlling for human capital. Panels A.I and B.I give our findings based on OLS regressions (repeated here for comparison). Panels A.II and B.II report our findings based on median (quantile .50) regressions estimated on the indicated samples. The raw gap is the difference in the predicted median male and female log wages based on the estimated median regression coefficients from separate male and female regressions under the human capital specification and the actual male and female means of the explanatory variables.[21] The second, the median gender log wage gap controlling for human capital, is the

[21] Note that, unlike OLS regressions, quantile regressions do not necessarily pass through the median of the dependent variable and the means of the independent variables. Thus, the predicted value of the male and female medians and the resulting gender gap is not necessarily equal to the actual male and female medians or the gender gap calculated from them.

difference in predicted median male and female log wages when both the male and female regressions are evaluated at the female means.

As may be seen in Panel A, median raw and human capital pay gaps for the sample of full-time employed workers are similar to those obtained using OLS regressions. Within each year, the size of the raw pay gap grows as we add individuals with less attachment to the labor force. Inspection of the predicted raw medians indicates that, on average, those included in the full-time employed sample are a positively selected group compared to those added to form our most inclusive sample (d).[22] Since we add considerably more females than males, the raw pay gap widens.

Table 4 provides some indirect evidence on the potential impact of selection on the slowdown in convergence in the gender pay gap in the 1990s. Focusing on a comparison of the trends for the medians for the full-time employed sample and the most inclusive of the three expanded samples, we see that the raw gap closed more slowly in the 1980s for the expanded sample (0.1535 log points) than for the full-time employed sample (0.1737 log points). Similarly, convergence in the unexplained gap was also slower for the expanded sample (0.1319 log points) than for full-time employed workers (0.1582 log points).

The results imply that, due to sample selection, the 1980s gains in women's relative wage offers were overstated. At first glance it might be expected that using the observed wages of workers with full-time jobs should have caused us to understate the gains, since, as Table 3 shows, the female full time work force was getting substantially larger over the 1980s, and median wage offers were lower among those without full-time jobs than among the full-time work force. The key to understanding why the selectivity-corrected offers closed more slowly than the observed wage offers in the 1980s lies in the changes in the degree of selectivity of the women included in full-time sample (group a) as the female labor force grew. Our results

[22] For men, predicted median log wages of full-time, employed workers (group a) were .10 to .14 log points higher than those added to the full-time employed to form our most inclusive group (d); for women, they were .22 to .29 log points higher.

suggest that female labor force growth over this period was positively selected,[23] and this is indeed consistent with considerable evidence on female labor force participation trends. For example, Juhn and Murphy (1997) find that employment gains for married women over the 1970s and 1980s were largest for wives of middle- and high-wage men who themselves tend to be more skilled.[24] This pattern is in turn related to the rising returns to skills over this period, which drew high-skilled women into the labor force. Our findings suggest that this positive selection characterized not only the observable characteristics of women in the labor force (as reflected in our results for the raw gap) but also their unobserved characteristics (as reflected in our results for the unexplained gap).

The selection adjustments had less impact for the 1990s, as might be expected based on the slower growth in the female labor force for that period. Convergence in the raw gap was faster in the expanded sample, where the gender gap fell by 0.0997 log points, than in the full-time employed sample, where it decreased by 0.0867 log points. This may reflect the large entry of relatively low-skilled, female single-family heads during this decade about which there is a sizable literature (e.g., Blank 2000; and Meyer and Rosenbaum 2001). Female gains in the gap controlling for human capital were also somewhat faster in the expanded sample (0.0187 log points) than the full-time sample (0.0078 points).

Can sample selectivity help explain the slowdown in convergence between male and female wages in the 1990s? Table 4 suggests that it is indeed part of the explanation. Specifically, the last two columns of Panel B compare changes in the raw and human capital-corrected gender pay gap in the 1990s and the 1980s. Looking at trends for the medians for our most restricted sample, the full-time employed, the raw pay gap converged 0.0870 log points more slowly in the 1990s than in the 1980s, and the difference between the two decades in the human capital corrected pay gap was even greater, closing 0.1504 log points more slowly in the

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[23] The estimated wage offers for women not included in group (a) were 25.2 percent lower than those in group (a) in 1979, but 33.2 percent lower in 1989—again indicating that the full-time employed had become more positively selected relative to those not included.

[24] See also Blau (1998) and references therein.

1990s than in the 1980s. However, in our most inclusive sample (d), the raw gap closed 0.0538 log points more slowly in the 1990s, and human capital corrected gap closed 0.1133 log points more slowly. The comparison across the two samples implies that as much as 0.0332 log points (i.e. 0.0870-0.0538) of the 0.0870 log point less rapid closing of the raw pay gap among the full-time employed in the 1990s was due to sample selection. Table 4 shows a comparable effect of selection on the human capital-corrected gender pay gap: 0.0371 log points of the 0.1504 log point less rapid closing of the human capital-corrected gender pay gap in the 1990s was due to sample selection. This implies that sample selection can explain about 25% (i.e., 0.0371/0.1504) of the slowdown in the narrowing of the unexplained pay gap (in the human capital specification) that we observe among the full-time employed. While this is a significant effect, our examination of selection does not alter our conclusion, based on OLS regressions for the full-time employed sample, that there was considerably less convergence in the unexplained gender pay gap in the 1990s than in the 1980s.[25]

B. Changes in Gender Differences in Unmeasured Characteristics and Labor Market Discrimination

As we have seen, even after our correction for sample selection, we conclude that the reduction in the unexplained gender pay gap was considerably smaller in the 1990s than in the 1980s. In this section we consider two possible sources of such a difference—slower reductions

[25] As noted earlier, in order to make conclusions about changes in the human capital-corrected pay gap where we include those whose wages are imputed as below or above median, we must assume that their wage offers are above median or below median, conditional on their human capital levels. This assumption is more likely to be valid for the group with less than a high school degree and less than eight years' full time experience (for whom we assume below conditional median wage offers) than for those with at least a college degree and at least eight years' full time experience (for whom we assume above conditional median wage offers). When we performed analyses like those in Table 4 adding only the less educated, less experienced group, the results were virtually identical: selection is estimated to account for 25% of the slowdown in the convergence in the unexplained pay gap, the same figure we obtained in Table 4, row d. Moreover, when we make no imputations and include only those for whom we observe a wage offer at some time in the past four years (group c in Tables 3 and 4), we obtain very similar results to those when we add the workers with imputed above or below median wage offers: row c of Table 4B shows that selection accounts for 27% of the slowdown in the closing of the unexplained gender pay; that is, (.1504-.1098)/.1504=.270, suggesting that our conclusions about selection are not sensitive to adding those with imputed wage offers.

in the gender difference in unmeasured characteristics and labor market discrimination in the 1990s. In the spirit of seeking as much homogeneity between the female and male samples when addressing these issues, we return our focus to the full-time employed sample.

With respect to unmeasured characteristics, it is possible that increases in women's commitment to the labor market and their employers was greater in the 1980s than the 1990s, even controlling for measured human capital and sector. Changes in such unmeasured characteristics are, by definition, difficult to measure. However, the possibility that such shifts played a role is given some support in Table 5, which shows annual hours of housework among full-time employed workers. Both for all workers and for married workers separately, the gender gap in housework hours closed much more rapidly in the 1980s than in the 1990s both absolutely and relatively. If housework reduces the effort one can put into a job (Becker 1985; Hersch and Stratton 1997), gender differences in potential effort on the job closed faster in the 1980s than the 1990s. Of course, the changes in housework hours could also have been a response to changing labor market opportunities; however, this does not invalidate the reasoning by which housework exerts an independent effect on labor market success. It is also possible that these differences in trends for gender differences in housework over the two decades are indicative of faster convergence over the 1980s in other unmeasured characteristics as well. The faster increase in female labor force participation in the 1980s, as well as the more rapid narrowing of the gender gap in experience in that decade are also suggestive of a greater increase in women's commitment to the labor force in the earlier decade.

It is also possible that discrimination decreased by more in the 1980s than in the 1990s. This might at first appear unlikely in that civil rights legislation passed in 1991 made the legal environment more favorable toward antidiscrimination lawsuits in the 1990s than in the 1980s. Specifically, the legislation allowed women to obtain compensatory and punitive damages for intentional discrimination whereas only compensatory damages had been available under Title

VII.[26] This contributed to a more rapid growth in job bias lawsuits over the 1990s, since representing defendants in such suits became more lucrative for private law firms operating on a contingency fee basis (Blau, Ferber and Winkler 2002, p. 243). Nonetheless, if women's labor force commitment changed more dramatically in the 1980s, as we speculated above, it is possible that employers' perceptions of women's labor force commitment also changed more dramatically in the 1980s. If so, one of the possible bases for statistical discrimination against women may have eroded faster in the 1980s.

An additional scenario whereby discrimination could have narrowed more slowly in the 1990s is related to the glass ceiling hypothesis mentioned above. The so-called glass ceiling problem refers to the explicit or, more likely, subtle barriers that inhibit women's progress at the highest echelons. If there is indeed such a problem, it may have had a greater negative impact on women in the 1990s as women's 1980s gains placed more of them into the higher-level positions where glass-ceiling barriers might hinder their further upward progression. The unexplained gender pay gaps estimated from quantile regressions presented in Table 6 are consistent with this possibility. The results for the unexplained gender pay gap from median regressions are quite similar to those based on OLS regressions (see, Tables 2A and 2B). The unexplained gap fell substantially in the 1980s, with relatively little further convergence in the 1990s. At the 90th percentile however, this pattern is even more pronounced, with the unexplained gap actually increasing in the 1990s, especially in the human capital specification. Of course, as in any analysis of this type, these findings may reflect, in whole or part, the impact of unmeasured characteristics rather than discrimination.

C. Shifts in Supply and Demand

[26] The 1991 law also reinstated the original judicial interpretation of Title VII of the 1964 Civil Rights Act that in disparate impact cases (i.e., cases in which an apparently neutral employment practice has an adverse impact on women or minorities), the burden of proof rests with the employer to show the business necessity of the practice. A 1989 Supreme Court decision had shifted to the plaintiff the burden of proof of showing that the disparate impact resulted from a specific business practice, and it also lowered the defendant's rebuttal standard from one of showing business necessity to one of showing that the practice merely contributed importantly to the firm's goals (Gould 1993, p. 240).

In this section we consider the possibility that less favorable changes in supply and demand for women during the 1990s than in the 1980s contributed to slower convergence in the unexplained gap during the 1990s. We proceed in two steps. We first develop a simple supply and demand model and use it to simulate the implied shifts in supply and demand that are consistent with the observed changes in women's relative wages and employment, based on consensus estimates of the other relevant parameters (i.e., own and cross wage elasticities of supply for men and women, and male-female elasticities of substitution in production). These estimates assume that supply and demand shifts fully account for the difference in the human capital-corrected wage gains of women between the two periods. We then provide some direct estimates of demand shifts based on observed changes in employment in occupation-industry cells that may be compared to the step one estimates of the required changes in demand that would be necessary to account fully for the observed differences in convergence in the unexplained gap between the two periods.

Let us begin by considering the following CES aggregate production function[27]:

$$(6) \qquad Y=[(A_f L_f)^p + (A_m L_m)^p]^{1/p},$$

where Y is output, L_f and L_m are respectively the quantity of female and male labor employed, A_f and A_m are demand shift terms, and p is related to σ, the elasticity of substitution between men and women, as follows:

$$(7) \qquad \sigma=1/(1-p).$$

We can think of at least two types of imperfect substitution between men and women that could be characterized by equation (6). First, men and women may tend to do different jobs

[27] This discussion of substitution in production between women and men follows Acemoglu's (2002) analysis of skilled worker-unskilled worker substitution.

within firms, in which case σ would be a metric for the degree of substitution between female-type jobs (e.g., administrative support) and male-type jobs (e.g., production workers). Second, men and women may work in different industries, implying that σ can measure the substitution of industries with a disproportionately female workforce (e.g. ,personal services) for those with a disproportionately male workforce (e.g., mining). Similarly, the demand shift terms A_f and A_m may signify technological change disproportionately affecting female or male jobs within firms or changes in final demand for output that affect industries with disportionately female or male workforces.

Assuming profit maximization and competition, equation (6) implies that the female relative wage equals the female relative marginal product:

(8) $$\ln(W_f/W_m) = [(\sigma-1)/\sigma]\ln(A_f/A_m) - (1/\sigma)\ln(L_f/L_m),$$

where W_f and W_m are respectively the average female and male wage rates.

On the supply side, suppose that we have the following functions determining the log of female and male labor supply:

(9) $$\ln L_f = \ln B_f + e_f \ln W_f + e_{fm} \ln W_m$$

(10) $$\ln L_m = \ln B_m + e_m \ln W_m + e_{mf} \ln W_f,$$

where B_f and B_m are, respectively, female and male labor supply shift terms, e_f and e_m are, respectively, female and male own wage labor supply elasticities, and e_{fm} and e_{mf} are, respectively, female and male cross wage labor supply elasticities. These labor supply equations can be derived from family utility or individual utility maximization models (Killingsworth and Heckman 1986) and assume that all family income comes from earnings (thus the male wage rate is a sufficient statistic for the potential nonlabor income available for women and vice versa). Note that the cross wage terms in (9) and (10) combine the leisure complementarity-substitution effect with the other family income effect in labor supply, since these are uncompensated labor supply equations. Our empirical implementation of this framework will take account of the fact that not all workers are married (see below).

Combining equations (8)-(10), we have the following expression for female relative wages, assuming market clearing:

(11) $$\ln (W_f/W_m) = (\sigma+e_{Tf})^{-1} [D_f - S_f - (e_{Tf}-e_{Tm})\ln W_m],$$

where $e_{Tf}=e_f-e_{mf}$, $e_{Tm}=e_m-e_{fm}$, $D_f=(\sigma-1)\ln(A_f/A_m)$, and $S_f=\ln(B_f/B_m)$.[28]

And, using (8) and (11), we can solve for the implied female relative demand and supply shift terms:

(12) $$D_f = \sigma\ln(W_f/W_m) + \ln(L_f/L_m)$$

(13) $$\begin{aligned} S_f &= D_f - (\sigma+e_{Tf})\ln(W_f/W_m) - (e_{Tf}-e_{Tm})\ln W_m \\ &= \ln(L_f/L_m) - e_{Tf}\ln(W_f/W_m) - (e_{Tf}-e_{Tm})\ln W_m. \end{aligned}$$

While equations (12) and (13) are written for a single time period, if the demand and supply elasticities remain constant, then we can express the change in the demand and supply shifts as functions of the changes in the gender pay ratio, the gender ratio in labor supply, and the male wage level. Based on the actual changes in female relative wages, female relative labor input and male real wages, we may recover the implied shifts in female relative demand and supply curves based on consensus estimates of the relevant parameters. The labor supply

[28] The female relative demand shift term is $(\sigma-1)\ln(A_f/A_m)$ rather than simply $\ln(A_f/A_m)$ because the latter is in output units, while multiplying by $(\sigma-1)$ transforms the shift into employment units. Note also that female labor augmenting technical change, which would be expressed as an increase in A_f, leads to an increase in the demand for female labor only if the elasticity of substitution is greater than one, a point made by Acemoglu (2002) in the context of the relative demand for skilled labor.

literature provides estimates for own and cross wage elasticities of supply, while labor demand studies provide estimates of the male-female elasticity of substitution in production.

For our estimates of own wage elasticities, we draw on three sources. First, Blundell and MaCurdy (1999) report the median across 18-20 estimates of own wage labor supply elasticities in various recent studies as 0.08 for men and 0.78 for married women. Second, Jacobsen (1998) summarizes existing work as showing a median male labor supply elasticity of -0.09 and a female elasticity of 0.77. And third, Filer, Hamermesh and Rees (1996) characterize the middle-level estimates of labor supply elasticities as equaling 0.0 for men and 0.80 for women. Based on these sources, we assume a value for own wage elasticity of labor supply of 0 for men and 0.78 for women. For the cross wage elasticities, Killingsworth (1983) reports a median spouse wage elasticity of 0.13 for married men's labor supply and -0.08 for married women's labor supply. In the PSID in 1990, roughly 72% of full-time employed men and 57% of full-time employed women were married, spouse present (Census definition). In computing e_{mf} and e_{fm}, then, we multiply these cross-elasticities by .72 and .57 respectively to account for the fact that the overall gender pay gap estimate combines both married and unmarried workers.

Regarding demand-side substitution, in his major review of research in this area Hamermesh (1993) listed only two studies that directly estimate the elasticity of substitution in production between men and women (σ). First, Layard (1983, p. 524) found that for British manufacturing for the 1949-69 period, the elasticity of substitution of men 21 years and over for women 18 years and over was 2.0. Second, Lewis (1985) found that in Australia over the 1975-81 period, the substitution elasticity of men over 21 for women over 21 was 2.29. A recent study by Weinberg (2000) adds to these two by estimating the male-female elasticity of substitution for the US for the 1970-94 period. He obtains an estimate of 2.4, which is remarkably similar to the elasticities obtained for Australia and Britain.[29] We use the midpoint, 2.29, of the existing

[29] Other studies examine the elasticity of complementarity (c), which in our context is the elasticity of the female/male relative wage with respect to the male/female relative employment level, holding marginal cost and other factor levels constant (see, for example, Borjas 1986a and b; and Grant and Hamermesh 1981). When there are only two factors of production, $\sigma=1/c$, but with more than two factors, this no longer necessarily holds (Hicks 1970). Since the studies reporting the elasticity of complementarity all have several factors of production other than

estimates of σ in our simulations. But in view of the paucity of research on male-female substitution, we examine the sensitivity of our conclusions with respect to alternative assumptions about the magnitude of σ. We caution the reader that our simple model abstracts from other factors of production (e.g., capital) and aggregates male and female inputs of different age and education levels. Our goal is simply to determine whether a supply and demand framework is plausible in explaining the slowdown in wage convergence between men and women in the 1990s.

The final inputs we need in order solve the first difference versions of (12) and (13) are changes in: female relative wages, female relative labor input, and male wages. To abstract from compositional changes in the labor force, the effects of which were investigated above, we control for human capital in estimating these wage changes. Thus, the female relative wage in a given year is obtained by evaluating the difference in the male and female wage regression coefficients using the female characteristics. Specifically, this is $(H_m-H_f)X_f$, where H_m and H_f are respectively vectors of male and female median human capital log wage regression coefficients and X is a vector of female means of the explanatory variables. The male wage is the predicted wage using each year's male wage equation applied to the 1990 sample of men (i.e., evaluated at the 1990 male means of the explanatory variables), in order to control for compositional changes in the male work force. We use the selectivity-bias corrected estimates of the wage regression coefficients from the most inclusive sample (Table 4, sample d). However, our results are qualitatively similar when we base them on OLS estimates of the human capital-corrected wage changes.

Table 7 gives the results of simulations based on three assumed values for σ: 2.29 (the median of the three values cited above), a high value of 3.0, and a low value of 1.0. In addition, implied demand and supply shifts are shown for both efficiency unit and hours measures of labor input. The results are qualitatively similar in each case. First, the female relative supply curve

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adult men and women (as do Layard 1983 and Lewis 1985), we cannot recover the relative wage elasticity of female relative demand (i.e., the substitution elasticity) from these studies.

shifted to the right in both the 1980s and the 1990s, but with a much smaller shift in the latter period. Second, there was a very large rightward shift in female relative demand in the 1980s that more than outweighed the supply shift; the rightward shift in female demand was much smaller in the 1990s. Thus, while the rightward shift in both the supply and demand curves diminished in the 1990s, the slowing of the female demand shift from the 1980s to the 1990s was much greater than the slowing of the supply shift.

The results in Table 7 suggest that technological, organizational and industrial composition changes were much more favorable for women in the 1980s than the 1990s. We can provide some more direct evidence on this issue by examining the degree to which changes in the industrial-occupational structure of employment favored women in the 1980s and the 1990s. To do this, we compute demand indexes similar to those specified by Katz and Murphy (1992). Following Katz and Murphy (1992), we construct industry-occupation cells and view the "output" of particular occupation groups as an intermediate product. A relative demand index, $\ln(1+\Delta DEM_f)$, was computed for women relative to men for the two time periods 1980-90 and 1990-99:

(14) $$\Delta DEM_f = \Sigma_o c_{of}(\Delta E_o/E_f),$$

where o refers to occupation-industry cell, c_{of} is the female share of the labor input in occupation-industry cell o over the pooled sample 1980, 1990 and 1999, ΔE_o is the difference between the 1990 and 1980 or 1999 and 1990 share of total labor input employed in cell o, and E_f is the 1980 or 1990 share of total labor input accounted for by women. The demand index thus measures the degree to which 1980-90 or 1990-99 shifts in occupation-industry structure favored women, using pooled 1980, 1990 and 1999 weights.

Estimates of such demand indexes are likely to be biased, so caution must be taken in interpreting the empirical results. When labor input is measured in hours or employment, the index will understate the shift in demand for women that would have occurred at constant relative wages, since women's wages rose more than men's over the sample period. This understatement will be more severe in the 1980s when women's relative wages were rising faster than in the 1990s. However, when labor input is measured in efficiency units (earnings), depending on the overall elasticity of demand for labor, the index could overstate or understate the shift in demand for women at constant relative wages. With inelastic labor demand, the index will overstate the shift toward women, while with elastic labor demand, the index will understate this shift; if the labor demand elasticity is -1, the index will accurately show the shift in labor demand at constant wages. In his review of many studies of labor demand, Hamermesh (1993) suggests that the elasticity of labor demand is less than zero but greater than -1, with a likely range of -0.15 to -0.75. This suggests that earnings based measures of labor demand shift will overstate the shift toward women during this period and will do so by more in the 1980s than the 1990s, in contrast to hours based measures. A perhaps greater source of bias, is that, the index does not take into account within industry-occupation cell demand changes. For example, it is possible that within each cell, physical strength became less important, and the relative demand for women rose. The probable importance of this factor leads us to conclude that both work hour and efficiency unit specifications of the demand index could underestimate true demand increases for women. We will return to this issue below.

In computing the demand indexes, we use 1980, 1990 and 1999 March CPS data because the CPS sample sizes allow us to construct more detailed industry-occupation cells than the PSID. We include part-time and full-time nonagricultural workers, and both the self-employed and wage and salary workers. However, because of the difficulty in measuring self-employment income, earnings-based measures of labor income include only wage and salary earnings. As noted, the base shares of female labor input (c_{of}) are computed using pooled 1980, 1990 and 1999 samples. In pooling these CPS files, we adjusted the CPS sampling weights so that each year receives the same weight. We obtained similar results using either the 1980, 1990 or 1999 female shares as our base. We use three alternative disaggregations by sector. First, we disaggregate sector by 43 mostly 2-digit industries. Demand shifts based on industry alone provide a between-industry demand shift measure. Second, we construct 129 industry-occupation cells based on the same 43 industries crossed with three occupational categories: (a) professionals and managers; (b) clerical and sales workers; and (c) craft, operative, laborer and service occupations. Third, we construct 215 industry-occupation cells based on the same 43 industries now crossed with five occupational categories: (a) professionals, (b) managers; (c) clerical and sales workers; (c) craft, operative, and laborer occupations; and (d) service occupations. Comparing demand indexes using industry-occupation cells and those using only industry can shed light on within-industry demand shifts. Moreover, comparing the five-occupation with the three-occupation specification can provide some evidence on the importance of within industry-occupation cell shifts.

Table 8 shows the results of these computations. For both definitions of labor input and each of the industry-occupation breakdowns, demand shifts were favorable toward women in the 1980s. Estimated demand shifts for the 1990s based on industry are also positive, although smaller than for 1980; those based on industry-occupation cells are close to zero and negative in two cases. Before considering the differences between the trends over the 1980s and 1990s in greater detail, a comment is in order about the between industry vs. the within industry-occupation cell estimates. For the 1980s, between industry demand shifts are estimated to be only slightly less favorable to women than estimates based on industry-occupation cells, while in the 1990s, between industry demand shifts are more favorable to women than those based on industry-occupation cells. This means that within industry occupational employment shifts were, on net, only slightly favorable to women in the 1980s, and unfavorable to women in the 1990s.. Inspection of the data revealed that this was principally due to the clerical and sales category for which demand was estimated to have only slightly increased over the 1980s and to have decreased in the 1990s. This outcome for the 1990s is consistent with a decrease in the demand for clerical workers with technological changes like word processing programs, computerized data processing, automatic teller machines, etc. However, it may also to some extent reflect the movement of women out of clerical jobs as better opportunities became available.

For supply and demand shifts to account for the larger closing of the unexplained gap in the 1980s, demand shifts should be more favorable to women in the 1980s than in the 1990s. This is indeed what is consistently indicated by the shift-share results in Table 8. For example, based on the estimates including an industry-occupation breakdown (rows B and C), demand shifts were 0.0346 to 0.0409 log points larger in the 1980s than in the 1990s. These estimated differences between the two decades are smaller than those required by our simulations in Table 7 to account fully for the slower closing of the unexplained gap in the 1990s. Moreover, within each decade, the estimated demand shifts in Table 8 are generally smaller than the shift in female supply implied by our Table 7 simulations. However, it is certainly possible that the shift-share analysis understates the true growth in demand, and particularly the extent of faster growth in the 1980s.

One obvious factor is that it is possible that a finer break down of industry-occupation categories would produce a greater difference in the trends between the two decades. This is at least suggested by the fact that our estimate of the difference between the two decades is larger when we take occupation into account than when we only look at industry. Moreover, it is possible that the kinds of gender-biased increases in the demand for intellectual skills discussed by Welch (2000) manifested themselves within industry-occupation cells. One indicator of the increased demand for "brains" over "brawn" is the growth in the incidence of computer use at work. The observation that women are more likely than men to use computers at work suggests that women as a group may have benefited from shifts in demand associated with computerization. Autor, Katz and Krueger (1998) for example note that the groups that had the most rapid increase in computer usage in the 1980s and early 1990s (the highly educated, whites, white collar workers and women) also had the largest wage increases. While the interpretation of this correlation is under some dispute (DiNardo and Pischke 1997), the finding suggests that growing computer use has raised the demand for women. Diffusion of computers likely also benefited women because computers restructure work in ways that de-emphasize physical strength (Weinberg 2000). Consistent with these arguments, Weinberg (2000) found for the

1984-93 period that, within industry-occupation cells, growth in overall computer usage in the cell increased women's share of hours worked among both computer users and nonusers.

Computerization rose more rapidly in the 1980s than in the 1990s and hence this may be a factor in explaining the slowdown in convergence in the 1990s. Friedberg (2003) reports that computer use increased from 24.4 percent of workers in 1984 to 37.3 percent in 1989, for an annual rate of increase of 8.9%; in contrast, the annual increase between 1989 and 1997 was only 3.9% (p. 514). Combining Weinberg's estimates of the impact of increased computer use on the female hours share with Friedberg's data on the growth in computer usage, we estimate that rising computer use increased women's share of hours by 0.0765 log points over the 1980s compared to 0.0295 log points over the 1990s under Weinberg's "high estimates," and 0.0470 log points in the 1980s compared to 0.0181 log points in the 1990s under his "low estimates."[30] This suggests a plausible source of within industry-occupation demand shifts favoring women relative to men to a greater extent in the 1980s than in the 1990s that is not captured by our shift-share analysis. While even adding these estimates to those presented in Table 8, we would still fall short of the demand shifts required by the simulation, this finding may be indicative of other factors positively affecting the demand for women within industry-occupation cells.

Finally, as noted above, the effects of industry, occupation and union coverage shown in Table 2B, taken together, are consistent with a slowdown in the growth of female demand in the 1990s. Specifically, Table 2B shows that women's relative industry-occupation location and union status changes together contributed to a 0.0476 log point closing in the gender wage gap in the 1980s, but to only a 0.0211 log point closing in the 1990s, with both occupational shifts and deunionization, in particular, contributing less to convergence in the 1990s. The smaller contribution of occupational shifts was due to men's greater loss of craft and operator jobs in the

[30] Friedberg provides data on computer use only for 1984, 1989, 1993, and 1997. The estimates in the text use linear interpolation to obtain computer use in 1998 and assume 0 incidence of computer use in the workplace in 1979. The latter is consistent with Autor, Katz and Krueger's (1998) observation that the IBM PC was introduced in 1981 and the Apple II in 1977. If we instead use linear interpolation to estimate 1979 computer use, we estimate that rising computer use increased women's share of hours by 0.0268 log points (Weinberg low estimate) to 0.0437 log points (Weinberg high estimate) over the 1980s; and 0.0181 log points (Weinberg low estimate) to 0.0295 log points (Weinberg high estimate) over the 1990s.

1980s than the 1990s; and men also lost union jobs more rapidly in the earlier period. Technical change has been widely cited as a factor in the shrinking of blue collar employment (e.g., Katz and Murphy 1992) and is likely to also be a significant cause of deunionization, as computers make it easier to substitute away from relatively unionized routine manual jobs (Autor, Levy and Murnane 2003).

VI. Conclusion

This paper has used PSID data to study the slowdown in the convergence of female and male wages in the 1990s compared to the 1980s. After decades of near constancy, between 1979 and 1989 the female/male hourly pay ratio rose by 17.8 percent—from 63.2 to 74.5 percent. However, convergence slowed in the 1990s, with the ratio rising to 79.7 in 1998, an increase of 7.2 percent on a ten-year basis. We first decomposed the slowdown in convergence into a portion due to changes in women's relative human capital levels and other measured characteristics; a portion that was unexplained by such changes in gender differences in measured characteristics; and a portion due to changes in overall prices in the labor market.

Our decompositions showed that women improved their relative human capital to a comparable extent in the 1980s and the 1990s. In the 1980s this upgrading consisted entirely of rising experience and, consistent with what might be expected based on the slowing growth in women's labor force participation rates in the 1990s, decreases in the gender gap in experience contributed considerably less to wage convergence in the 1990s. However, rising relative educational attainment of women played a much larger role in the 1990s, and thus, the sum of the effects of education and experience was similar in the two decades. In contrast, while occupational upgrading and deunionization contributed to women's relative wage gains in both decades, the impact of these factors was greater in the 1980s. While women increased their relative representation in managerial and professional jobs and reduced their relative representation in clerical and service jobs at about the same pace in both periods, men moved out of (or lost) craft and operator jobs at a faster rate in the 1980s. And, as the pace of deunionization slowed for both men and women in the 1990s, the gender difference in the rate of deunionization also declined. Thus, slowing convergence in sectoral location in the 1990s is part of the explanation for the slowdown in wage convergence. The results of our decompositions also indicate that the price of skills and returns to location in favorable sectors of the economy cannot explain why the gender pay gap fell faster in the 1980s than in the 1990s. These prices changed to the detriment of women in the 1980s and had very little effect in the 1990s.

Controlling for human capital, sector, and the prices of measured and unmeasured labor market skills, we found that women made much larger gains in relative wages in the 1980s than in the 1990s. This difference, which is "unexplained" by our regression analyses, was sufficient to more than fully account for the slowdown in wage convergence in the 1990s. We then considered the factors that may have contributed to these changes in the convergence of the unexplained gender pay gap, including changes in labor force selectivity, changes in the gender difference in unmeasured characteristics and labor market discrimination, and changes in the favorableness of supply and demand shifts. We present some evidence consistent with each of these factors suggesting that each may have played a role in explaining the observed trends.

First, we considered the role of labor force selectivity. Using median regression methods, we conclude that gender convergence in wage offers over the 1980s was significantly overstated by the focus on employed women in full-time jobs. This suggests that female labor force growth over the 1980s was positively selected; a finding that is consistent with studies of female labor force participation trends over that period. The much smaller growth in the female labor force over the 1990s was found to be slightly negatively selected, perhaps reflecting the large entry of relatively low-skilled, female single-family heads during this decade. Taking the trends for both periods into account, our results imply that as much as 25 percent of the apparent slowdown in convergence in the unexplained gender pay gap was an artifact of labor force selection. While this is a significant effect, the selection results do not alter our conclusion, based on OLS regressions for the full-time employed sample, that there was considerably less convergence in the unexplained gender pay gap in the 1990s than in the 1980s.

Second, we examined evidence on changes in the gender difference in unmeasured characteristics and labor market discrimination. We found some indirect evidence in support of both of these factors. Specifically, we found that the gender gap in housework hours closed much more rapidly in the 1980s than in the 1990s both absolutely and relatively. While these changes could have in part been a response to changing labor market opportunities, it is also possible that they represent, at least in part, exogenous behavioral shifts and that they are indicative of faster convergence over the 1980s in other unmeasured characteristics as well. The faster increase in female labor force participation in the 1980s, as well as the more rapid narrowing of the gender gap in experience in that decade are also suggestive of a greater increase in women's commitment to the labor force in the earlier decade. With respect to discrimination, we speculated that if there was there was indeed a greater growth in women's labor force commitment in the 1980s, one of the possible bases for statistical discrimination against women may have eroded faster in that decade. We also presented some evidence from quantile regressions that was consistent with a greater negative effect of glass ceiling barriers on women's relative wages in the 1990s, as women's 1980s gains placed more of them into the higher-level positions where glass-ceiling barriers might hinder their further upward progression. Of course, as in any analysis of this kind, these findings could reflect the impact of unmeasured characteristics rather than discrimination.

Finally, it is likely that due to technological change and changes in the composition of final demand, the demand for labor in sectors where women predominate rose faster in the 1980s than in the 1990s. To study this issue, we constructed a supply-demand model of women's relative wages and relative employment. We used consensus estimates of labor supply and production substitution elasticities, along with the observed changes in women's relative employment and relative wages (adjusted for selection and human capital) to infer the shifts in female relative demand and supply consistent with the observed trends. The model implied that a large reduction in demand shifts favoring women in the 1990s compared to the 1980s was the major factor explaining the slowdown in wage convergence. We obtained some direct evidence on these shifts by constructing shift-share demand indexes using CPS data for 1980-1990 and 1990-1999. Based on changes in the overall occupational-industrial distribution of employment, we conclude that demand did indeed shift more favorably toward women in the 1980s than the 1990s. Although the magnitudes of our indexes were much smaller than required by the theoretical model, we noted that demand shifts favoring women could also operate within industry and occupation cells and thus not be measured by our analysis. We presented some evidence on one factor, computerization, which proceeded more rapidly in the 1980s than in the 1990s and likely contributed to increasing demand for women within occupation-industry cells.

Appendix A: The Decomposition of Changes in the Gender Pay Gap

Following JMP's notation, suppose that we have for male worker i and year t a male wage equation:

$$(1A) \qquad Y_{it} = X_{it}B_t + \sigma_t\theta_{it},$$

where Y_{it} is the log of wages; X_{it} is a vector of explanatory variables; B_t is a vector of coefficients; θ_{it} is a standardized residual (i.e. with mean zero and variance 1 for each year); and σ_t is the residual standard deviation of male wages for that year (i.e. its level of male residual wage inequality). As will be clear in our explanation of the implementation of the decomposition below, following JMP, we do not impose normality on the distribution of residuals.

The male-female log wage gap for year t is:

$$(2A) \qquad D_t \equiv Y_{mt} - Y_{ft} = \Delta X_t B_t + \sigma_t \Delta\theta_t$$

where the m and f subscripts refer to male and female averages, respectively; and a Δ prefix signifies the average male-female difference for the variable immediately following. Equation (2A) states that the pay gap can be decomposed into a portion due to gender differences in measured qualifications (ΔX_t) weighted by the male returns (B_t), and a portion due to gender differences in the standardized residual from the male equation ($\Delta\theta_t$) multiplied by the money value per unit difference in the standardized residual (σ_t). We also perform the decomposition using the female wage equations and obtain similar results.[31] Note that the final term of (2A) corresponds to the "unexplained" differential in a standard decomposition of the gender differential when the contribution of the means is evaluated using the male function.

The difference in the gender pay gap between two years 0 and 1 (i.e., 1979-89 and 1989-98) can then be decomposed using (2A):

$$(3A) \qquad D_1 - D_0 = (\Delta X_1 - \Delta X_0)B_1 + \Delta X_0(B_1 - B_0) + (\Delta\theta_1 - \Delta\theta_0)\sigma_1 + \Delta\theta_0(\sigma_1 - \sigma_0).$$

The first term of (3A) is the Observed X's Effect; the second term is the Observed Prices Effect; the third term is the Gap Effect and the fourth term is the Unobserved Prices Effect. Following

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[31] Datta Gupta, Oaxaca and Smith (2003) suggest performing Juhn, Murphy Pierce decompositions on pooled male and female wage samples. We chose not to do this because the coefficients in such equations confound compositional effects (e.g. the female composition of dummy variable categories) and true returns to human capital and rents.

JMP, we estimate the gap and the unmeasured prices effects empirically using the entire distribution of male and female wage residuals in each year. Specifically, to compute $(\Delta\theta_1-\Delta\theta_0)\sigma_1$, we first give each woman in year 0 a percentile number based on the ranking of her wage residual (from the year 0 male wage regression) in the year 0 distribution of male wage residuals. We then impute the wage residual of each woman in year 0, given her percentile ranking in year 0 and the distribution of male wage residuals in year 1. So, taking the 1979-89 comparison as an example, if a woman ranks at the 20th percentile of the male distribution of wage residuals in 1979, she would be given the residual corresponding to the 20th percentile of the 1989 male distribution of wage residuals. The average of these imputed residuals (multiplied by -1) is our estimate of $\Delta\theta_0\sigma_1$. (Recall that the mean male residual is always zero.) The average 1989 female residual from the 1989 male wage regression (multiplied by -1) constitutes our estimate of $\Delta\theta_1\sigma_1$. The difference between the actual and imputed residuals yields $(\Delta\theta_1-\Delta\theta_0)\sigma_1$. The fourth term of (3), $\Delta\theta_0(\sigma_1-\sigma_0)$, is obtained analogously. Note, again, that by using the actual distribution of male residuals, we do not impose normality on the residual distribution.

Appendix B: Computation of Actual Full Time and Part Time Experience

Whenever people join the PSID panel for the first time as a head or wife, they are asked how many years they worked since they were 18 years old, and of these years, how many involved full-time work. In addition, in 1976 and 1985, the PSID asked all heads and wives these two questions regardless of when they joined the panel. The answers to these questions form the base from which we calculate actual full time experience and part time experience (which is defined as total experience minus full time experience). Once we have these initial values for full time and part time experience, we fill in the period between the date these questions were asked and the focal year (e.g. 1980, 1990 or 1999) by using the longitudinal work history data collected for all heads and wives in the years after they join the panel or in the years after 1976 or 1985, whichever comes last. For example, suppose one joined the panel in 1987 and we want to compute full time and part time experience as of the 1990 survey. These were collected as of 1987. We then add 1 to total labor market experience for each year between 1987 and 1990 in which the person worked positive hours and 1 for full time experience for each year the person worked at least 1500 hours. Part time experience is increased by 1 for each year there were positive but less than 1500 hours of employment.

This procedure allows us to fill in the experience history of all respondents for all years of the survey with one exception: the PSID began skipping alternate years with the 1999 survey, meaning that there was no 1998 survey. We therefore have no information on annual work hours between 1997 and 1998. To fill in this missing year of experience, we use the 1999 male and female samples and estimate logit models separately by gender for having positive work hours and for working at least 1500 hours in the previous year and in the year preceding the 1997 survey (for those who joined in 1999 and therefore have no data from the 1997 survey, we already have their complete work experience data). The explanatory variables include the race, schooling and experience variables in the human capital model, plus a marital status indicator and the number of children living with the respondent. To estimate part time and full time experience for the missing year (i.e. the year between 1997 and 1999), we average the two predicted values for these variables from the 1999 logit and the 1997 logit.

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Figure 1: Gender Gap, Log Hourly Earnings, by Percentile, Full-Time Workers, PSID

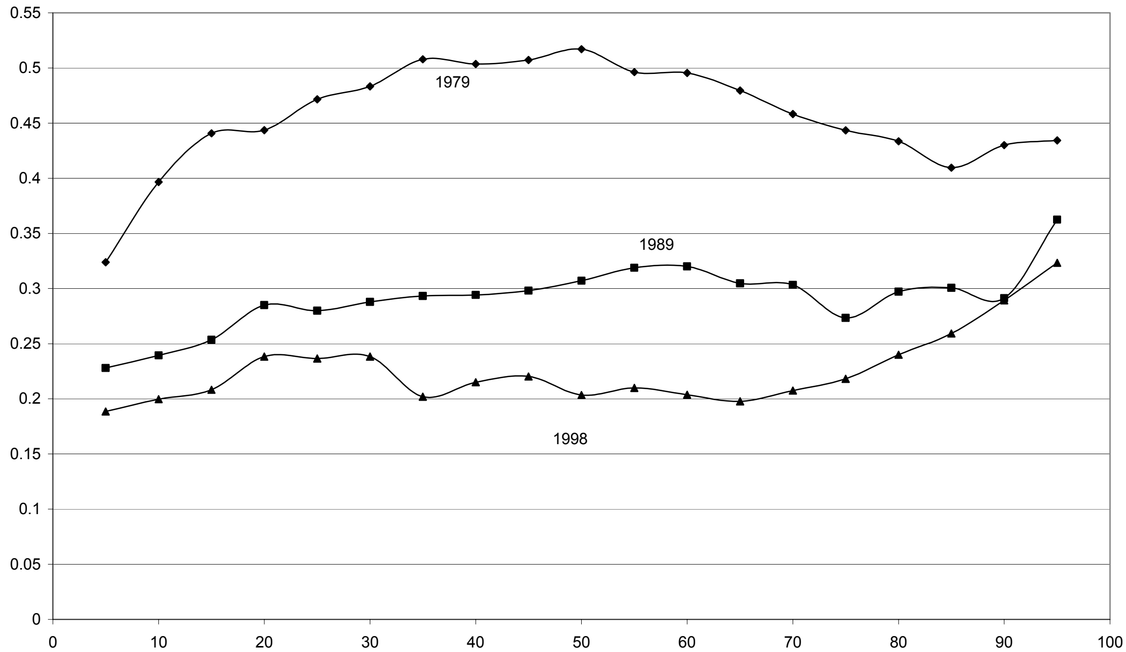

Table 1: Overview of Wage Trends (1983 Dollars), 1979, 1989 and 1998

	1979	1989	1998	Changes (Average Annual Change X 10) 1979-89	1989-98
Log Male Wage	2.3841	2.3335	2.3535	-0.0506	0.0222
Std. Dev.	(0.5060)	(0.5688)	(0.6012)	0.0628	0.0360
90-10 Differential	1.1703	1.4173	1.4608	0.2470	0.0483
Log Female Wage	1.9255	2.0387	2.1261	0.1132	0.0971
Std. Dev.	(0.4836)	(0.5432)	(0.5663)	0.0596	0.0257
90-10 Differential	1.1369	1.3655	1.3710	0.2286	0.0061
Gender Log Wage Differential	0.4586	0.2948	0.2274	-0.1638	-0.0749
Implied Female/Male Pay Ratio	0.6322	0.7447	0.7966	0.1125	0.0577
Mean Female Percentile in the Male Wage Distribution[a]	24.31	35.16	38.93	10.85	4.19

Note: Table contains full-time, nonfarm wage and salary workers aged 18-65 years from the Michigan Panel Study of Income Dynamics. Wages are computed as annual earnings divided by annual work hours. Years refer to the period during which income was earned. The Implied Female /Male Pay Ratio is (exp (ln wf)/exp(ln wm)), where ln wf and ln wm are, respectively, the average log female and log male wage.

[a]Computed by assigning each woman a percentile ranking in the indicated year's male wage distribution and calculating the female mean of these percentiles.

Table 2A: Decomposition of Changes in the Gender Pay Gap, 1979-89 and 1989-98: Descriptive Statistics

	Human Capital	Full
Male Residual Standard Deviation[a]		
1979	0.4411	0.4036
1989	0.4693	0.4211
1998	0.5092	0.4577
Female Residual Standard Deviation[b]		
1979	0.4204	0.3694
1989	0.4279	0.3766
1998	0.4741	0.4172
Male Residual 90-10 Differential[a]		
1979	1.0279	0.9159
1989	1.1242	1.0283
1998	1.2051	1.0468
Female Residual 90-10 Differential[b]		
1979	0.9389	0.8448
1989	1.0637	0.9219
1998	1.1522	0.9790
Mean Female Residual from Male Wage Regression		
1979	-0.3458	-0.2035
1989	-0.2003	-0.0943
1998	-0.2088	-0.0935
Implied Gender Wage Ratio (Adjusted for Measured Xs)		
1979	0.7077	0.8159
1989	0.8185	0.9100
1998	0.8116	0.9107
Mean Female Residual Percentile		
1979	27.00	34.57
1989	36.71	43.15
1998	37.68	44.18

[a] Residuals from a male wage regression.
[b] Residuals from a female wage regression.

Notes: The human capital specification includes controls for race, education and experience. The full specification includes, in addition, controls for occupation, industry and collective bargaining coverage. See Table A2 for variable means and Table A3 for regression results.

Table 2B: Decomposition of Changes in the Gender Pay Gap, 1979-89 and 1989-98: Decomposition Results (Average Annual Changes X 10)

	1979-89		1989-98		(1989-98) - (1979-89)	
	Human Capital	Full	Human Capital	Full	Human Capital	Full
Change in Differential (D_1 - D_0)	-0.1638	-0.1638	-0.0748	-0.0748	0.0890	0.0890
Observed X's						
All X's	-0.0488	-0.0923	-0.0560	-0.0676	-0.0072	0.0247
Education variables	0.0002	-0.0013	-0.0354	-0.0291	-0.0356	-0.0278
Experience variables	-0.0528	-0.0458	-0.0192	-0.0165	0.0336	0.0293
Occupation variables	----	-0.0287	----	-0.0190	----	0.0097
Collective Bargaining	----	-0.0218	----	-0.0074	----	0.0144
Industry variables	----	0.0029	----	0.0053	----	0.0024
Observed Prices						
All B's	0.0305	0.0378	-0.0283	-0.0064	-0.0588	-0.0442
Education variables	0.0042	0.0043	0.0026	0.0022	-0.0016	-0.0021
Experience variables	0.0248	0.0216	-0.0322	-0.0267	-0.0570	-0.0484
Occupation variables	----	-0.0181	----	0.0536	----	0.0717
Collective Bargaining	----	0.0074	----	-0.0005	----	-0.0078
Industry variables	----	0.0218	----	-0.0359	----	-0.0577
Unexplained Differential	-0.1455	-0.1092	0.0094	-0.0009	0.1549	0.1083
Gap Effect	-0.1801	-0.1279	-0.0063	-0.0074	0.1738	0.1205
Unobserved Prices	0.0346	0.0187	0.0157	0.0065	-0.0189	-0.0122

Notes: The human capital specification includes controls for race, education and experience. The full specification includes, in addition, controls for occupation, industry and collective bargaining coverage. See Table A2 for variable means and Table A3 for regression results.

Table 3: Fraction of Adult Population With Earnings Observations Under Different Sample Inclusion Rules

	1979		1989		1998	
Sample Inclusion Rule	Men	Women	Men	Women	Men	Women
a) Full Time Employed Workers	0.8331	0.4098	0.7982	0.4970	0.8107	0.5252
b) All with Hourly Earnings Observations	0.9378	0.6804	0.9158	0.7572	0.9176	0.7692
c) All with Hourly Earnings Observations in the Last Four Years	0.9737	0.8057	0.9695	0.8657	0.9567	0.8699
d) c) + those with (16+ yrs Educ and 8+ yrs Exp) or (<12 yrs Educ and < 8yrs Exp)	0.9763	0.8591	0.9764	0.9018	0.9639	0.9053

Source: PSID.

Table 4: Changes in Gender Pay Gaps at the Mean for Full-time Workers and at the Median Under Different Sample Inclusion Rules

	Raw Gap	Gap Controlling for Human Capital	Raw Gap	Gap Controlling for Human Capital	Raw Gap	Gap Controlling for Human Capital
A. Gender Pay Gaps	1979		1989		1998	
I. Mean (Full-time Employed Workers)	0.4586	0.3458	0.2948	0.2003	0.2274	0.2088
II. Median, Sample Inclusion Rule:						
a) Full Time Employed Workers	0.4790	0.3658	0.3052	0.2076	0.2272	0.2006
b) All with Hourly Earnings Observations	0.5209	0.3462	0.3893	0.2223	0.3176	0.2264
c) All with Hourly Earnings Observations in the Last Four Years	0.5456	0.3512	0.4244	0.2348	0.3430	0.2289
d) c) + those with (16+ yrs Educ and 8+ yrs Exp) or (<12 yrs Educ and < 8yrs Exp)	0.6201	0.3849	0.4666	0.2530	0.3769	0.2362
	(Average Annual Changes X 10)					
B. Chages in the Gender Pay Gaps	1979-1989		1989-1998		(1989-98) - (1979-89)	
I. Mean (Full-time Employed Workers)	-0.1638	-0.1455	-0.0748	0.0094	0.0890	0.1549
II. Median, Sample Inclusion Rule:						
a) Full Time Employed Workers	-0.1737	-0.1582	-0.0867	-0.0078	0.0870	0.1504
b) All with Hourly Earnings Observations	-0.1317	-0.1239	-0.0796	0.0046	0.0520	0.1285
c) All with Hourly Earnings Observations in the Last Four Years	-0.1212	-0.1164	-0.0905	-0.0066	0.0307	0.1098
d) c) + those with (16+ yrs Educ and 8+ yrs Exp) or (<12 yrs Educ and < 8yrs Exp)	-0.1535	-0.1319	-0.0997	-0.0187	0.0538	0.1133

Source: PSID. Raw Gap is the difference in predicted mean or median log male and log female wage, which is H_mX_m-H_fX_f, where H_m and H_f are respectively vectors of male and female mean (Row I) or median (Rows IIa-d) human capital log wage regression coefficients and X_m and X_f are respectively male and female means for the vector of explanatory variables, which include a dummy for white, years of schooling, dummies for college degree and advanced degree, and part-time and full-time actual experience and their squares. The Gap Controlling for Human Capital is $(H_m-H_f)X_f$.

Table 5: Annual Hours of Housework, Full Time Employed Wage and Salary Workers

	Men	Women	Difference: Male-Female	Ratio: Male/Female
A. All Workers				
1979	380.04	872.02	-491.98	0.436
1989	391.59	705.47	-313.88	0.555
1998	358.07	639.83	-281.76	0.560
Changes ($YEAR_1$ - $YEAR_0$)*				
1979-89	11.55	-166.55	178.10	0.119
1989-98	-37.25	-72.94	35.69	0.005
B. Married Workers				
1979	365.746	998.007	-632.26	0.366
1989	394.578	806.394	-411.82	0.489
1998	358.193	723.340	-365.15	0.495
Changes ($YEAR_1$ - $YEAR_0$)*				
1979-89	28.83	-191.61	220.44	0.123
1989-98	-40.43	-92.28	51.86	0.007

*Average Annual Change X 10.

Source: PSID. Sample includes full time nonfarm wage and salary workers.

Table 6: Unexplained Gender Pay Gaps Based on Quantile Regressions, 1979-89 and 1989-98

	Human Capital	Full	Human Capital	Full	Human Capital	Full
A. Unexplained Gender Pay Gap	1979		1989		1998	
50th Percentile	0.3658	0.2106	0.2076	0.1007	0.2005	0.0762
90th Percentile	0.3770	0.2539	0.2090	0.1439	0.2691	0.1655
B. Changes in the Unexlained Gender Pay Gap	Average Annual Change X 10					
	1979-89		1989-98		(1989-98) - (1979-89)	
50th Percentile	-0.1582	-0.1099	-0.0079	-0.0272	0.1503	0.0827
90th Percentile	-0.1680	-0.1100	0.0668	0.0240	0.2348	0.1340

Notes: The human capital specification includes controls for race, education and experience. The full specification includes, in addition, controls for occupation, industry and collective bargaining coverage. The unexplained gap is calculated as $(B_M - B_F)X_F$, where B_M and B_F are vectors of coefficients from male and female quantile regression equations and X_F is a vector of female means.

Table 7: Estimated Female Demand and Supply Shifts (Based on Selectivity Corrected Wage Changes) (Average Annual Changes X 10)

	σ = 2.29		σ = 3		σ = 1	
	1979-1989	1989-1998	1979-1989	1989-1998	1979-1989	1989-1998
$d\ln(W_f/W_m)$	0.1319	0.0187	0.1319	0.0187	0.1319	0.0187
$d\ln(W_m)$	-0.1108	-0.0230	-0.1108	-0.0230	-0.1108	-0.0230
$d\ln(L_f/L_m)$ efficiency units	0.2467	0.0967	0.2467	0.0967	0.2467	0.0967
$d\ln(L_f/L_m)$ work hours	0.1479	0.0164	0.1479	0.0164	0.1479	0.0164
D_f (efficiency units)	0.5488	0.1395	0.6424	0.1528	0.3786	0.1154
S_f (efficiency units)	0.2373	0.1007	0.2373	0.1007	0.2373	0.1007
D_f (work hours)	0.4500	0.0593	0.5436	0.0725	0.2798	0.0351
S_f (work hours)	0.1385	0.0204	0.1385	0.0204	0.1385	0.0204

Notes: σ is the male-female elasticity of substitution in production; $d\ln(W_f/W_m)$ is the change in the human capital corrected female/male log wage differential based on median regressions estimated on the most inclusive sample (See Table 6, sample d); $d\ln(W_m)$ is the predicted change in the real male median wage for the 1990 male sample using the 1980, 1990 and 1999 male median regression coefficients; $d\ln(L_f/L_m)$ is the change in the ratio of total female to total male labor input, including the self employed and part time workers; D_f and S_f are respectively the implied female demand and supply shifts. All estimates assume a female own wage labor supply elasticity (e_f) of 0.78; a male own wage labor supply elasticity (e_m) of 0; a female labor supply elasticity wrt male wages (e_{fm}) of -0.0456; and a male labor supply elasticity wrt female wages (e_{mf}) of 0.0936.

Table 8: Demand Indexes for Women, Based on Industry-Occupation Shifts (Annual Changes X 10)

	Labor Input in Efficiency Units		Labor Input in Work Hours	
Industry-Occupation Breakdown	1980-90	1990-99	1980-90	1990-99
A. 43 Industries	0.0515	0.0404	0.0276	0.0204
B. 43 Industries x 3 Occupations	0.0545	0.0136	0.0322	-0.0044
C. 43 Industries x 5 Occupations	0.0556	0.0148	0.0329	-0.0017

Source: March CPS for 1980, 1990 and 1999. The 43 industries are largely the 2 digit industries as defined by the Census. The 3 occupation breakdown includes: (a) professionals and managers; (b) clerical and sales workers; (c) craft, operative, laborer and service occupations. The 5 occupation breakdown disaggregates category (a) into (a1) professionals and (a2) managers and category (c) into (c1) craft, operative and laborer occupations and (c2) service workers.

Table A1: Overview of Wage Trends (1983 Dollars), 1979, 1989 and 1998, CPS Data

				Changes (Average Annual Change X 10)	
	1979	1989	1998	1979-89	1989-98
Log Male Wage	2.2475	2.2233	2.2626	-0.0242	0.0437
	(0.5409)	(0.5947)	(0.6064)	0.0538	0.0130
Log Female Wage	1.8109	1.9159	2.0161	0.1050	0.1113
	(0.4689)	(0.5383)	(0.5647)	0.0694	0.0293
Log Wage Differential	0.4366	0.3074	0.2465	-0.1292	-0.0677
Implied Female/Male Pay Ratio	0.6462	0.7354	0.7815	0.0891	0.0513
Mean Female Percentile in the Male Wage Distribution[a]	26.08	34.96	37.99	8.88	3.37

Note: Table contains full-time, nonfarm wage and salary workers aged 18-65 years from the Current Population Survey. Wages are computed as annual earnings divided by annual work hours. Years refer to the period during which income was earned. The implied female /male pay ratio is (exp (ln wf)/exp(ln wm)), where ln wf and ln wm are, respectively, the average log female and log male wage.

[a]Computed by assigning each woman a percentile ranking in the indicated year's male wage distribution and calculating the female mean of these percentiles.

Table A2: Means for the Regression Samples, PSID

	1979		1989		1998	
	Men	Women	Men	Women	Men	Women
white	0.870	0.841	0.885	0.831	0.866	0.819
schooling, years	12.699	12.666	13.295	13.256	13.450	13.677
college degree only	0.160	0.152	0.203	0.177	0.219	0.230
advanced degree	0.069	0.040	0.082	0.069	0.066	0.073
full time experience (yrs)	18.305	11.743	18.280	14.008	19.839	16.290
full time experience squared	478.718	221.334	447.901	273.692	508.039	357.277
part time experience (yrs)	1.204	2.448	1.667	2.697	1.423	3.027
part time experience squared	6.924	19.856	10.150	24.927	7.222	26.264
union coverage	0.349	0.216	0.239	0.185	0.202	0.173
occupation variables						
physician	0.002	0.000	0.004	0.003	0.005	0.002
other medical	0.004	0.040	0.005	0.037	0.006	0.041
accountant	0.014	0.012	0.014	0.014	0.018	0.025
teacher k-12	0.022	0.079	0.017	0.081	0.025	0.103
teacher college	0.014	0.013	0.013	0.012	0.009	0.016
architect	0.053	0.003	0.054	0.011	0.044	0.008
technician	0.042	0.023	0.066	0.054	0.065	0.045
public advisor	0.019	0.022	0.018	0.026	0.020	0.040
lawyer	0.005	0.000	0.007	0.003	0.008	0.008
other professional	0.006	0.008	0.006	0.019	0.011	0.016
manager	0.162	0.085	0.172	0.129	0.167	0.156
sales	0.049	0.033	0.066	0.033	0.063	0.043
clerical	0.052	0.349	0.053	0.315	0.054	0.278
foreman	0.037	0.003	0.021	0.006	0.028	0.005
other craft	0.210	0.009	0.180	0.018	0.178	0.013
protective service	0.030	0.005	0.053	0.012	0.057	0.014
transportation equip. operator	0.060	0.010	0.066	0.006	0.063	0.002
other operator	0.131	0.150	0.108	0.091	0.091	0.056
laborer	0.045	0.006	0.045	0.007	0.041	0.015
other service worker*	0.043	0.150	0.032	0.122	0.048	0.112

*Omitted cateory for the occupation dummy variables.

Table A2: Means for the Regression Samples, PSID (ctd)

	1979		1989		1998	
	Men	Women	Men	Women	Men	Women
Industry Variables						
mining	0.013	0.001	0.009	0.003	0.009	0.001
metal manufacturing	0.047	0.013	0.034	0.009	0.028	0.010
machinery	0.080	0.063	0.070	0.047	0.046	0.027
motor vehicles	0.069	0.030	0.049	0.014	0.042	0.021
other durables	0.055	0.021	0.049	0.023	0.042	0.015
food, tobacco	0.029	0.012	0.021	0.011	0.022	0.011
textiles, apparel	0.017	0.052	0.009	0.031	0.007	0.014
paper	0.008	0.005	0.009	0.005	0.011	0.004
chemicals	0.037	0.018	0.034	0.017	0.032	0.013
other nondurables	0.005	0.008	0.006	0.006	0.006	0.004
construction	0.083	0.006	0.082	0.010	0.095	0.008
transportation	0.069	0.014	0.056	0.025	0.063	0.015
communications	0.018	0.029	0.022	0.018	0.031	0.016
utilities	0.028	0.008	0.034	0.008	0.028	0.006
retail trade	0.092	0.123	0.114	0.115	0.095	0.099
wholesale trade	0.028	0.018	0.052	0.027	0.046	0.024
finance, ins. real estate	0.040	0.078	0.044	0.096	0.046	0.089
repair services	0.014	0.002	0.015	0.000	0.025	0.002
business services	0.011	0.020	0.037	0.031	0.048	0.042
personal services	0.010	0.022	0.012	0.031	0.006	0.025
recreation	0.008	0.002	0.012	0.004	0.016	0.006
publishing	0.025	0.016	0.021	0.024	0.014	0.019
medical services	0.027	0.159	0.032	0.164	0.035	0.174
educational services	0.063	0.154	0.069	0.184	0.082	0.226
professional sevices	0.029	0.041	0.018	0.027	0.015	0.027
public administration**	0.095	0.085	0.092	0.070	0.111	0.100

**Omitted category for the industry dummy variables.

Source: PSID. Sample includes full time employed wage and salary nonagricultural workers age 18-65. Year refers to earnings date; explanatory variables are measured as of the survey date (i.e. 1980, 1990 and 1999).

Table A3: Log Hourly Earnings Regression Results

	1979 Men		1979 Women		1989 Men		1989 Women		1998 Men		1998 Women	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE
A. Human Capital Spec												
white	0.1056	0.0253	0.1021	0.0268	0.1589	0.0275	0.1457	0.0241	0.1818	0.0313	-0.0100	0.0293
schooling yrs	0.0550	0.0046	0.0759	0.0066	0.0798	0.0062	0.0990	0.0072	0.0721	0.0076	0.0848	0.0092
college degree only	0.0611	0.0307	0.0462	0.0385	0.1351	0.0332	0.1243	0.0361	0.1712	0.0382	0.1643	0.0419
advanced degree	0.0851	0.0420	0.2204	0.0607	0.1790	0.0448	0.2175	0.0498	0.2956	0.0560	0.2635	0.0599
full time experience (yrs)	0.0440	0.0028	0.0303	0.0033	0.0475	0.0031	0.0508	0.0034	0.0431	0.0039	0.0447	0.0041
full time experience squared	-0.0007	0.0001	-0.0005	0.0001	-0.0007	0.0001	-0.0009	0.0001	-0.0007	0.0001	-0.0007	0.0001
part time experience (yrs)	0.0003	0.0068	0.0018	0.0052	-0.0034	0.0062	-0.0053	0.0044	-0.0106	0.0103	0.0057	0.0060
part time experience squared	0.0002	0.0004	0.0001	0.0003	0.0006	0.0003	0.0004	0.0002	0.0019	0.0010	-0.0002	0.0003
R^2	0.2399		0.2441		0.3193		0.3792		0.2824		0.2990	
Sample size	2816		1922		2894		2290		2336		1804	
B. Full Spec												
white	0.0734	0.0240	0.0690	0.0244	0.1015	0.0257	0.1182	0.0222	0.1166	0.0293	-0.0174	0.0269
schooling yrs	0.0444	0.0048	0.0439	0.0065	0.0611	0.0061	0.0511	0.0071	0.0480	0.0075	0.0497	0.0088
college degree only	0.0403	0.0303	-0.0189	0.0379	0.1182	0.0319	0.1347	0.0347	0.1710	0.0367	0.1469	0.0395
advanced degree	0.1445	0.0447	0.1681	0.0590	0.2511	0.0447	0.2886	0.0488	0.3279	0.0558	0.2245	0.0580
full time experience (yrs)	0.0379	0.0027	0.0246	0.0030	0.0385	0.0029	0.0427	0.0031	0.0363	0.0036	0.0371	0.0038
full time experience squared	-0.0006	0.0001	-0.0004	0.0001	-0.0005	0.0001	-0.0008	0.0001	-0.0006	0.0001	-0.0006	0.0001
part time experience (yrs)	-0.0001	0.0064	0.0004	0.0048	-0.0050	0.0057	-0.0014	0.0040	-0.0088	0.0095	0.0056	0.0056
part time experience squared	0.0002	0.0004	0.0000	0.0002	0.0009	0.0003	0.0002	0.0002	0.0017	0.0009	-0.0004	0.0003
union coverage	0.2207	0.0190	0.1691	0.0229	0.2764	0.0208	0.2495	0.0231	0.2687	0.0271	0.2200	0.0303
physician	0.7873	0.1929			0.1363	0.1414	0.2444	0.1508	0.9306	0.1605	0.6871	0.2321
other medical	0.0447	0.1385	0.5149	0.0521	0.3071	0.1253	0.4387	0.0507	0.4500	0.1367	0.5882	0.0628
accountant	0.4959	0.0820	0.2718	0.0857	0.3289	0.0876	0.3061	0.0747	0.4661	0.0901	0.2153	0.0765
teacher k-12	0.2907	0.0741	0.4199	0.0551	0.2524	0.0837	0.3007	0.0496	0.1185	0.0852	0.2755	0.0554
teacher college	0.2752	0.0828	0.5176	0.0861	0.3034	0.0886	0.3290	0.0827	0.3677	0.1135	0.1107	0.0913
architect	0.5569	0.0590	0.5734	0.1780	0.3819	0.0644	0.4670	0.0855	0.6320	0.0703	0.4287	0.1186
technician	0.3928	0.0569	0.4510	0.0647	0.3506	0.0592	0.3775	0.0446	0.5016	0.0627	0.3598	0.0590
public advisor	0.2447	0.0726	0.3942	0.0693	0.1038	0.0778	0.3877	0.0584	0.1641	0.0852	0.2341	0.0621
lawyer	0.7053	0.1260	0.8205	0.7415	0.4410	0.1143	0.1991	0.1500	0.7607	0.1292	0.7789	0.1291
other professional	0.3730	0.1077	0.1769	0.1032	0.3772	0.1121	0.4115	0.0702	0.5562	0.1048	0.4140	0.0901
manager	0.4414	0.0466	0.3938	0.0417	0.3634	0.0537	0.3174	0.0362	0.5402	0.0538	0.3730	0.0435
sales	0.2953	0.0568	0.1501	0.0566	0.1448	0.0601	0.3044	0.0533	0.4311	0.0629	0.2097	0.0629
clerical	0.1886	0.0540	0.1703	0.0327	0.0201	0.0601	0.1393	0.0310	0.2125	0.0638	0.0481	0.0403
foreman	0.3916	0.0584	0.2720	0.1608	0.1655	0.0747	0.1983	0.1098	0.3458	0.0763	0.1390	0.1518
other craft	0.2403	0.0456	0.2349	0.0985	0.1519	0.0534	0.0658	0.0659	0.3345	0.0550	-0.0171	0.0973

Table A3: Log Hourly Earnings Regression Results (ctd)

	1979 Men		1979 Women		1989 Men		1989 Women		1998 Men		1998 Women	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE
B. Full Spec (ctd)												
protective service	0.1515	0.0674	0.1600	0.1340	0.0703	0.0657	0.3210	0.0832	0.3101	0.0690	0.4509	0.0948
transport equip. oper	0.1083	0.0539	0.1609	0.0965	-0.0860	0.0588	-0.0056	0.1090	0.1832	0.0634	-0.3911	0.2127
other operator	0.1431	0.0479	0.1125	0.0455	0.0124	0.0562	-0.1274	0.0452	0.2066	0.0602	-0.1071	0.0676
laborer	0.1437	0.0559	0.2327	0.1199	-0.0051	0.0616	-0.1743	0.1030	0.1064	0.0678	0.0156	0.0904
mining	0.0781	0.0746	0.2918	0.2466	0.1882	0.0911	0.2386	0.1491	0.3168	0.1092	0.2905	0.3320
metal mfg.	0.0804	0.0489	0.4721	0.0846	0.0479	0.0570	0.0494	0.0950	0.2032	0.0707	-0.0962	0.1086
machinery	0.0606	0.0425	0.0308	0.0517	0.1565	0.0471	0.0198	0.0537	0.1580	0.0602	0.1057	0.0746
motor vehicles	0.1645	0.0443	0.2850	0.0605	0.1913	0.0518	0.0953	0.0751	0.2374	0.0618	0.1466	0.0822
other durables	0.0402	0.0469	0.0029	0.0706	0.0309	0.0520	-0.0972	0.0657	0.0568	0.0630	-0.0134	0.0934
food, tobacco	0.0835	0.0559	0.0216	0.0866	0.0111	0.0660	-0.0703	0.0860	0.0510	0.0756	-0.0517	0.1037
textiles, apparel	-0.1706	0.0683	-0.1610	0.0592	-0.1158	0.0938	-0.1733	0.0617	0.0332	0.1239	-0.2086	0.1021
paper	0.0275	0.0944	0.1491	0.1317	0.0926	0.0899	-0.1321	0.1181	0.1951	0.1014	0.2264	0.1709
chemicals	0.1138	0.0515	0.2262	0.0736	0.1124	0.0577	0.1240	0.0706	0.2503	0.0676	0.2021	0.0968
other nondurables	0.0756	0.1162	-0.1669	0.1045	-0.3764	0.1095	-0.0323	0.1110	-0.1928	0.1260	-0.1308	0.1558
construction	0.0491	0.0434	0.2932	0.1184	0.0461	0.0470	0.0530	0.0878	0.0509	0.0528	-0.0816	0.1153
transportation	0.0667	0.0445	0.0600	0.0817	0.0630	0.0497	-0.0070	0.0637	0.0595	0.0556	0.1011	0.0898
communications	0.1430	0.0651	0.2300	0.0611	0.1398	0.0650	0.1766	0.0681	0.3089	0.0672	0.1481	0.0872
utilities	0.0453	0.0561	0.2195	0.1011	0.1370	0.0557	0.0188	0.0967	0.3296	0.0696	0.0070	0.1340
retail trade	-0.0949	0.0422	-0.2062	0.0429	-0.1201	0.0447	-0.3577	0.0431	-0.0705	0.0524	-0.2984	0.0498
wholesale trade	0.0529	0.0570	-0.0559	0.0720	0.0645	0.0518	-0.0988	0.0599	0.0824	0.0615	-0.0657	0.0741
finance, ins. real est.	-0.0130	0.0516	0.0410	0.0446	0.0653	0.0527	0.0458	0.0423	0.2005	0.0597	0.0053	0.0497
repair svc	-0.0754	0.0743	-0.4199	0.2239	-0.0846	0.0761	0.0009	0.3854	-0.0067	0.0773	-0.2217	0.2188
business svc	-0.0272	0.0802	0.1475	0.0686	0.0789	0.0541	-0.0046	0.0573	0.1799	0.0575	-0.0443	0.0610
personal svc	-0.0669	0.0858	-0.2254	0.0695	-0.0915	0.0823	-0.1676	0.0591	-0.0906	0.1318	-0.3929	0.0761
recreation	-0.2587	0.0917	0.1481	0.2096	-0.1234	0.0816	-0.2531	0.1300	-0.2460	0.0856	-0.3567	0.1366
publishing	0.1784	0.0589	0.0291	0.0777	-0.0117	0.0654	-0.1358	0.0623	0.0875	0.0896	-0.0260	0.0834
medical svc	-0.0171	0.0588	-0.0109	0.0434	-0.1065	0.0627	-0.1289	0.0412	0.0039	0.0685	-0.1344	0.0458
educational svc	-0.1758	0.0538	-0.0707	0.0449	-0.3261	0.0518	-0.2395	0.0417	-0.1183	0.0570	-0.2346	0.0462
professional svc	-0.1250	0.0565	-0.0110	0.0528	0.0746	0.0693	-0.0179	0.0596	0.0883	0.0910	-0.0064	0.0721
R^2	0.3637		0.4166		0.4520		0.5192		0.4204		0.4573	
Sample size	2816		1922		2894		2290		2336		1804	

Source: PSID. Sample includes full time employed wage and salary nonagricultural workers age 18-65. Year refers to earnings date; explanatory variables are measured as of the survey date (i.e. 1980, 1990, and 1999).

Table A4: Decomposition of Changes in the Gender Pay Gap, 1979-89 and 1989-98, CPS and PSID Samples, Potential Experience Specification

	PSID	CPS
A. Decomposition of Change 1979-89		
Change in Differential (D89-D79)	-0.1638	-0.1292
Observed X's	-0.0198	-0.0269
Observed Prices	0.0084	0.0022
Gap Effect	-0.1978	-0.1350
Unobserved Prices	0.0454	0.0306
Unexplained Differential (Gap Effect + Unobserved Prices Effect)	-0.1524	-0.1044
B. Decomposition of Change 1989-98 (average annual changes X 10)		
Change in Differential (D98-D89)	-0.0748	-0.0677
Observed X's	-0.0428	-0.0174
Observed Prices	0.0013	-0.0040
Gap Effect	-0.0520	-0.0494
Unobserved Prices	0.0187	0.0032
Unexplained Differential (Gap Effect + Unobserved Prices Effect)	-0.0333	-0.0462

Note: Wage equation includes white dummy variable, education, potential experience, and it square.