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Do Male-Female Wage Differentials Reflect Differences in the Return to Skill? Cross-City Evidence from 1980–2000†

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Male-female wage gaps declined significantly over the 1980s and 1990s, while returns to education increased. In this paper, we use cross-city data to explore whether, like the return to education, the change in the gender wage gap may reflect changes in skill prices induced by the diffusion of information technology. We show that male-female and education-wage differentials moved in opposite directions in response to the adoption of PCs. Our most credible estimates imply that changes in skill prices driven by PC adoption can explain most of the decline in the US male-female wage gap since 1980. (*JEL* J15, J24, J31, J71, O33, R23)

The US wage gap between men and women with similar characteristics has decreased significantly since 1980 (Figure 1), after exhibiting little trend for decades prior (Goldin 1990; O'Neill and Polacheck 1993). Many explanations have been proposed for this, including increased positive selection of women into the labor market (Mulligan and Rubinstein 2008), an improved match between women's actual and potential experience due to their greater labor force attachment (O'Neill and Polacheck 1993; Bailey, Hershblein, and Miller 2012), and decreased discrimination.[1] One especially intriguing observation is that the timing of the change matches quite closely the rise in the return to education over this period (Figure 1), leading some, notably Welch (2000), to conjecture that the two patterns may be driven by common underlying changes in relative skill prices.[2] Workers may bring

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[1] O'Neill and Polacheck (1993) and others also attribute some of the decline to a decrease in blue collar wages. Gender discrimination is often mentioned, but, as it is difficult to quantify, its importance is not usually empirically assessed. One exception is Blau and Kahn (2006), who look for indirect evidence whether the smaller residual decline in the male-female wage gap in the 1990s compared to the 1980s could be due to women reaching "glass ceilings" in the 1990s. Though they show some evidence in support of this, they also evaluate other interpretations, including changes in selection and the slowing rate of computerization.

[2] Another view is that rising returns to skill should have lowered women's relative wages, since women are lower in the wage distribution than men (Blau and Kahn 1997; Card and DiNardo 2002). This follows from viewing skill as a single index, which contrasts with the two attribute model that we pursue in this paper. Blau and Kahn (1997) did note that the higher rate of computer use among women than men suggested women may have actually benefitted from, rather than been harmed by, skill-biased technological change.

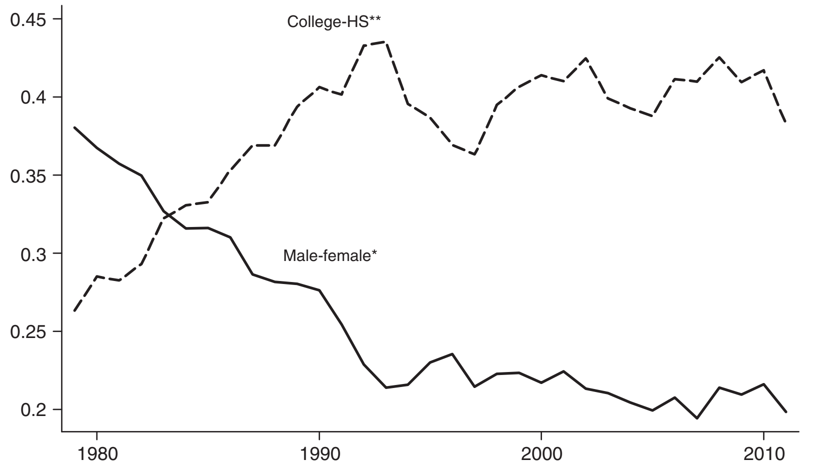

Figure 1. Adjusted Male-Female*, College-HS** Wage Gaps, 1979–2011

Notes: *Adjusted for gender × year × education (five groups) specific quartic in potential experience (age − yrsed (years of education) − 6), black and Hispanic dummies, post-1950 cohort, yrsed, and yrsed × post1950. Simple average of five education groups, evaluated at average female characteristics, 1979–2011. **Simple average of male and female adjusted college-high school (HS) wage gaps.

Source: Current popluation survey Merged Outgoing Rotation Groups

to the market, to use Welch's terminology, both "brains"—cognitive or interpersonal skills—and "brawn"—motor skills. If women and more educated workers are both well endowed with cognitive or interpersonal skills relative to physical skills—and the characteristics of the occupations they work in suggest that they are (Figure 2)—then an increase in the relative price of cognitive or interpersonal skills should cause the male-female wage gap to decrease at the same time as the return to education increases.[3]

The force most commonly associated with changing the relative price of skills in the post-1980 period is the adoption of information technology (IT). Thus, the suggestion is that changes in both the gender wage gap and the returns to education may have been driven by the diffusion of IT in the form of personal computers (PCs), due to its effect of the latent price of skills. Despite some support for this hypothesis, the literature on gender gaps appears to remain skeptical of its importance, perhaps because the existing evidence for it is either time-series or else does not directly analyze gender wage gaps.[4] The aim of this paper is to exploit variation across US

[3] This idea likely predates the observation made in Welch (2000). For example, Goldin (1990) discusses how similar kinds of technological change benefited women in a historical context, and also uses the terms "brains" and "brawn" to describe the changes in skill demands.

[4] Time series correlations are presented in Welch (2000) and Fortin and Lemieux (2000). Female employment share changes are also positively correlated with computer adoption across industries (Weinberg 2000). Black and Spitz-Oener (2010) found that a majority of women's relative wage increases in Germany between 1979 and 1999 can be accounted for by a large relative shift away from "routine cognitive" tasks which Autor, Levy, and Murnane (2003) found were associated with computerization. Bacolod and Blum (2010) show that the decline in wages in motor skills-intensive jobs, and the rise in wages and cognitive skill-intensive jobs can account for one-quarter of the decline in the male-female wage gap.

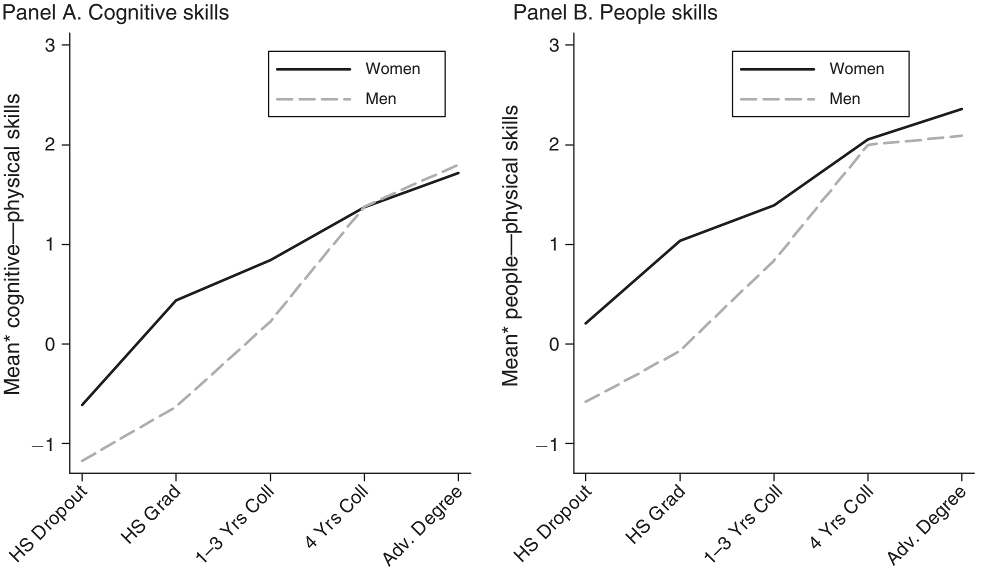

Figure 2. Relative Skills in Mean* Occupation by Gender, Education: 1980

Notes: *Weighted by annual hours worked, computed using 1980 census (5 percent public use). Occupational scores computed with 1971 CPS supplement containing fourth edition DOT scores (NAS 1981) and matched to 1980 occupation codes using Trieman crosswalk file. See online Appendix.

metropolitan areas to explore the hypothesis that the diffusion of information technology simultaneously explains movements in both the gender wage gap and the return to education through its effects on the relative price of latent skills.

A. *Preliminary Data Patterns*

In Figure 2, we document that differences in average occupational characteristics support the notion that women and more educated workers have a comparative advantage in cognitive and interpersonal skills relative to physical skills. Figure 2 is constructed using variables from the Fourth Edition Dictionary of Occupational Titles (DOT) as tabulated in the April 1971 Current Population Survey (National Academy of Sciences Committee on Occupational Classification and Analysis 1981) which provides information on the types of skills used in different occupations. We built standardized "cognitive," "people," and "physical" indexes using a linear combination of DOT variables that fit these themes (see online Appendix for details). We then constructed two relative indexes of brain versus brawn by taking the difference between each of our two brain indexes (cognitive, people) and our physical index.[5] Figure 2 presents a plot of the mean of these two indexes of brains

[5] The components of our indexes have a lot of overlap with the ones used in Bacolod and Blum (2010). For example, the "cognitive" index includes the three "general educational development" scores and the measure of the level of complexity of data tasks; the "people" index includes indicators for "dealing with people," "influencing people," and "direction, control, and planning;" and the "physical" score includes a measure of the strength requirements of the job. Full details of the indexes' construction appears in the online Appendix.

versus brawn by gender and education.[6] The figure shows a very similar pattern for the two indexes. We see that holding gender constant, the indexes increase with the amount of education, and for each education level, women have a higher index than men.[7] This pattern is consistent with previous "task-based" evidence of gender differences in comparative advantage (e.g., Baccolod and Blum 2010). Not shown in Figure 2 is the fact that these indexes also rise over time, potentially consistent with IT driving up relative demand for cognitive and interpersonal skills.

The conjecture pursued in this paper is that the diffusion of IT increased the relative price of brains versus brawn, and given that women and more highly educated individuals appear in Figure 2 to be relatively better endowed with this attribute, this should have caused the male-female wage differential to decrease most and the return to education to increase most in cities that adopted IT most intensively. Based on this idea, we begin by simply plotting changes in the college-high school differential and changes in the male-female wage gaps at the city level against the local rate of PC adoption, and see if this predicted pattern is visible. Figure 3 shows that, indeed, college-high school wage gaps rose more and male-female gaps fell more between 1980 and 2000 in areas that adopted more PCs per worker by 2000.[8]

While this simple observation provides some support for the hypothesis, the direction of causality is unclear. In particular, the adoption of a new technology is an endogenous process. To examine this hypothesis more credibly, therefore, we need to isolate forces that explain why certain cities adopted PCs more quickly than others. To this end, we will use insights from the endogenous technology adoption literature that suggests if PCs complement cognitive skills, then areas that were initially more educated should see faster adoption of PCs. This, in turn, should lead to greater change in the price of brains versus brawn.[9] Using this idea, Beaudry, Doms, and Lewis (2010) (hereafter, BDL) showed that PC use and college-high school wage gaps increased more in markets that were more educated at the onset of the diffusion of the PC, that is, in 1980. This result is reproduced in panels A and B of Figure 4. The question addressed in this paper is whether a similar pattern extends to the gender wage gap, with the idea that the male-female wage gap should respond in the opposite direction—it should fall faster in the initially more educated areas due to the fact that such areas adopted IT faster, causing the relative price of

[6] The means are weighted by hours worked in each gender by occupation cell, the weights having being estimated from the 5 percent public-use 1980 Census of Population (Ruggles et al. 2010). The weighted standard deviation across these cells is about 1.7 for both relative indexes.

[7] The differences across education groups and between men and women are statistically significant. In terms of absolute skills, there is no significant gender gap in the absolute level of the cognitive or people index, but a large and significant gap in the absolute physical skills index. See the online Appendix for details.

[8] The wage gaps, which were constructed using the 1980 and 2000 5 percent public use Censuses of Population, are adjusted to be between otherwise similar men and women in terms of potential experience, race, and education; and between more and less educated workers in terms of potential experience, race, and gender. The PC measure is adjusted for industry and firm size. Details are in the next section.

[9] One view of recent technological change is that the PC is a "revolutionary" technology (Caselli 1999) of discretely higher skill intensity than previous technology; its adoption therefore depends on comparative advantage—the relative price of (and therefore supply of) skill. This is also empirically supported in Beaudry and Green (2003, 2005). Autor, Levy, and Murnane (2003) also model computer adoption as responding to skill ratios, and we consider a version of their model in the online Appendix. Another view is that PCs are the latest example of ongoing improvements in the quality of capital that favor skilled workers that perhaps go back as much as a century (Goldin and Katz 2008).

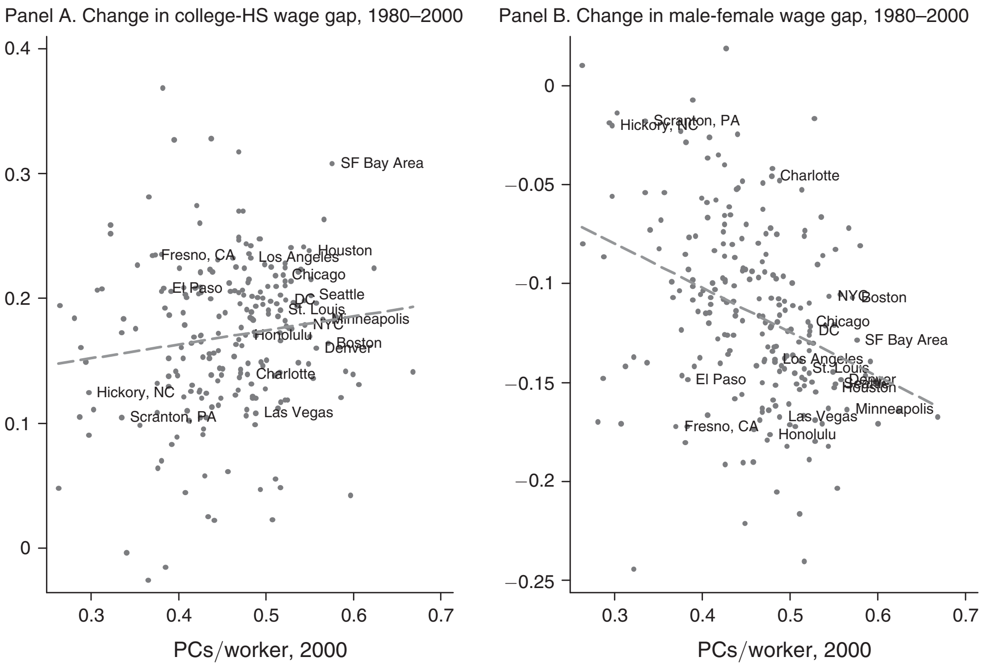

Figure 3. Change in Wage Gaps, 1980–2000, versus PCs/Worker, 2000

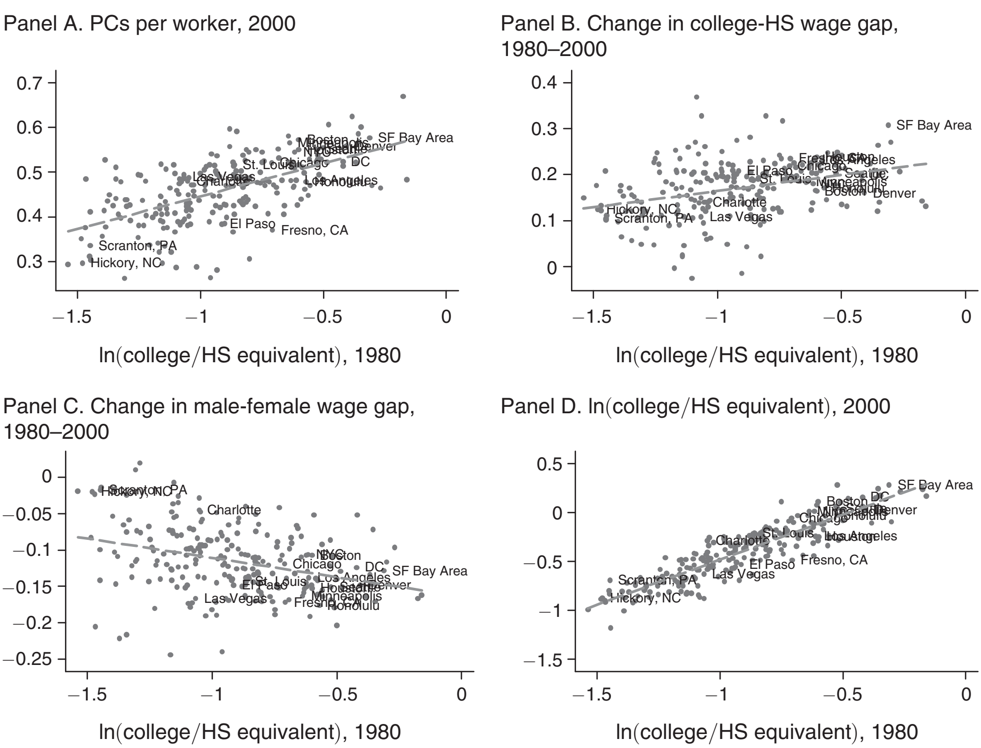

Figure 4. Reduced Forms with ln(College/HS Equivalent)

brawn versus brain to decrease. Panel C in Figure 4 plots this relationship, and we see that, indeed, the gender wage gap decreased most over the 1980–2000 period in cities that were most educated in 1980. In order to highlight that educational attainment is a feature of a city that does not respond quickly to contemporaneous events, in panel D of Figure 4, we plot the co-movement between 1980 and 2000 in a city's education attainment. In this we see that the relative education level of a city changes very little over time, which is comforting given that we want to interpret the education level of a city as of 1980 as a characteristic that can be treated as exogenous relative to subsequent PC adoption.

While Figures 3 and 4 suggest that gender and education wages gaps may have moved in opposite directions in response to differential propensities to adopt IT, there remains the possibility that a third factor drives the observed relationship. For example, an increase in the return to education might differentially induce more skilled women to enter the workforce;[10] a decline in blue-collar wages could decrease males' and less educated workers' wages (relative to women's and more educated workers'); younger, more educated cohorts of women might have higher wages because of greater labor force attachment. So the remaining sections of the paper will examine the robustness of the patterns highlighted in Figures 3 and 4 with the aim of providing support for a causal interpretation running from initial educational levels, through PC adoption, to changes in the male-female wage gap.

Our finding is that many of the other forces suggested in the literature appear to have, at best, a modest role in explaining the relationships in Figures 3 and 4, giving credence to the claim that the adoption of IT may have driven the fall in the male-female wage gap. Among other things, we find that industry mix controls (including durable manufacturing density) and the selection of women into the labor force can only account for a minor fraction of the differential changes in the male-female wage gap observed since 1980. Our estimates imply that most of the national-level (time series) reduction in the male-female wage differential since 1980 can be attributed to a change in latent skill prices induced by the diffusion of IT as captured by PC adoption.

I. Theory, Empirical Methods, and Data

As the discussion of Figures 3 and 4 implied, we will now examine more thoroughly the relationship between PC adoption and changes in both male-female and education wage gaps. The main instrument we will use to address the potential endogeneity of PC adoption is a measure of pre-PC era education mix. As is worked out formally in the online theoretical Appendix, if our pre-PC era measure of education is a valid instrument, then our cross-city IV estimates can be used to infer how much of the decline in the male-female wage gap at the aggregate level can be attributed to changing skill prices. One threat to this identification strategy come about if areas

[10] This is an alternative explanation for the simultaneous rise in the education wage gap and decline in the male-female wage gap that Mulligan and Rubinstein (2008) argue for; like us, they claim to account for most of the decline in the male-female wage gap since 1980. Note that this differs from our story, which relates to the *quality constant* male-female wage gap.

differ in the effectiveness of PC use, and this effectiveness is correlated with initial education levels. The online theory Appendix describes how this can bias OLS estimates downward in magnitude and bias IV estimates upward in magnitude. While such biases are possible, we will attempt to rule them out empirically, as best we can, in robustness checks.[11]

For the purposes of empirical implementation, we define "pre-PC" as 1980 and compute wages and skill supplies in this year using the 5 percent public-use version of the 1980 Census of Population (Ruggles et al. 2010). For "post-PC" we will examine both the 5 percent public use 2000 Census of Population, and the stacked 2009–2011 American Community Surveys (Ruggles et al. 2010); we will call the latter "2010" data. It is standard in papers on skill-biased technical change to aggregate workers to two skill groups, college and high school "equivalents," and so we define our skill mix measure as the log ratio of college to high school equivalent hours worked.[12] It was constructed using only data on those aged 16–65 with positive (potential) work experience (age − years of schooling − 6 > 0), not living in group quarters. Hourly wages were constructed for the subsample of these with positive wage and salary earnings and hours worked in the past year, without any self-employment earnings, currently employed, and not in school. Hourly wages were "Windsorized" to be between \$2 and \$200 in 1999 dollars.

Male-female wage gaps were constructed separately for the 230 metropolitan areas and for the five education groups—high school dropouts, high school graduates, those with some college education (but less than four years), four-year college graduates, and graduates with advanced degrees—that can be consistently identified across censuses.[13] As compositional changes are known to have substantially affected the gender wage gap over this period (e.g., Blau and Kahn 2006), wages are regression adjusted, separately by gender, education group, and year, for a quartic in potential work experience, and dummies for foreign-born, black, Hispanic, and being born after 1950 (where Lemieux (2006), describes a cohort break in trends in returns to schooling). To account for heterogeneity in years of education among workers in the dropout, some college, and advanced degree groups, we also include a linear control for years of education and its interaction with the dummy for being

[11] The use of this instrument also raises the question of what allows for stable differences in skill mix across locations. There are both equilibrium and nonequilibrium explanations for this. BDL attempt to rationalize differences in skill supply across cities with skill-specific differences in housing supply, which was a shorthand for amenities that were differentially valued by high- and low-skill workers. The idea that amenity differences across locations allowed for stable differences in skill mix was suggested by evidence in Black, Kolesnikova, and Taylor (2009). BDL's theory section concluded that while allowing for this mechanism would affect the magnitude of the results, it was unlikely to affect the direction. In addition, there is evidence that local labor markets may remain out of spatial equilibrium with other markets for quite some time (Beaudry, Green, and Sand 2013) and that labor markets adjust slowly to shocks (Blanchard and Katz 1992). BDL show, in particular, that many of the currently highly educated labor markets were also highly educated over a century ago, which could be consistent with either (equilibrium or nonequilibrium, slow adjustment) story.

[12] Our implementation follows Card (2009): dropouts are counted as 0.7 high school equivalents, high school as 1, and some college as 0.6; some college are counted as 0.4 college equivalents, and college graduates as 1. Note that this definition treats dropouts and graduates as perfectly substitutable, consistent with evidence in both Card (2009) and Goldin and Katz (2008).

[13] We matched census geographic variables to the 1999 definition of "consolidated" metropolitan areas. In the 1980 census, "high school" and "college" workers are defined as those who have completed exactly 12 years and 16 years of schooling, respectively, and in the 2000 census, are those who report being in the category "high school graduate" and "bachelor's degree."

born after 1950 for these groups.[14] To make the means interpretable, adjusted wages are centered on the predicted values for the average female characteristics (in our whole sample of metropolitan areas) in each year.[15]

The five education-specific adjusted male-female wage gaps are stacked in the regression and regressed on PCs per worker, as in

$$\Delta MFdiff_{ec} = \alpha_e + \phi^1 PC/L + \Gamma_e X_{ec} + \Delta\varepsilon_{ec}, \tag{1}$$

where $\Delta MFdiff_{ec}$ is the change in the (adjusted) male-female wage differential for education group e in area c; α_e are education group effects; PC/L is PCs per worker; and X_{ec} are controls, whose effects are potentially allowed to vary by education group. PCs per worker is computed from firm-level data collected by the marketing firm Harte-Hanks in 2000 and 2002 (which for simplicity we refer to as "2000" data), and is adjusted for three-digit (SIC) industry crossed with size category dummies. Note that the PC use measure is cross-sectional, but PC use was near zero in 1980, so our measure also represents (roughly) the intensity of PC adoption. We will show both OLS estimates and IV estimates of (1) using initial skill mix—ln $s_{c,1980}$, i.e., ln (college/HS equivalent) in 1980—as an instrument. Standard errors are calculated to be asymptotically robust to arbitrary error correlation within area.

Regrettably, we have no similar PC use measure for 2010. Therefore, for the longer time frame 1980–2010, we can examine only the reduced form relationship with initial skill mix and the change in the male-female wage gap as given by

$$\Delta MFdiff_{ec} = \alpha_e + \phi^2 \ln s_{c,1980} + \Gamma_e X_{ec} + \Delta\varepsilon_{ec}. \tag{2}$$

The other outcome we examine is the education wage gap, specifically, the simple average of male and female adjusted college-high school wage gaps. It comes from the same adjustment procedure described above. Recall that we want to examine whether it always responds in an opposite fashion to the male-female wage gaps.

Summary statistics on our metropolitan-level wage gap and skill mix measures are shown in Table 1. In each year there are 1,150 observations on the male-female wage gap from 230 metropolitan areas and 5 education groups. As has been documented elsewhere, the male-female wage gap declined between 1980 and 2000 by about 12 log points. This decline was largest between less educated men and women. Male relative wages declined further by 2010. Table 1 also shows there is "something to be explained"—there is variation in the change in the gender wage gap across labor markets, even within education group, which itself is perhaps a new fact. We now ask whether it is related to PC adoption and initial skill mix.

[14] In neither census is there literally a "years of education" variable, but categories of years (1980) or degrees (2000, 2010). Within these three education groups with heterogeneous education, the grouping of education is quite different in the two censuses. In both cases, we impute years from the midpoint of the categories in the group.

[15] In equation form, we estimate $\ln W_{iegct} = a_{egct} + \beta'_{egt} X_{iegct} + u_{iegct}$, where $\ln W_{iegct}$ is the natural log hourly wage of person i of education group e and gender g living in city c in year t, which is regressed on fixed effects, a_{egct}, and the adjustment variables, X_{iegct}, mentioned above. This is evaluated at the national female mean $\overline{X_{eft}}$, and, thus, the adjusted male-female wage gap in education group e, city c, and year t is given by $MFdiff_{ect} = a_{emct} - a_{efct} + \left(\hat{\beta}_{emt} - \hat{\beta}_{eft}\right)' \overline{X_{eft}}$.

Table 1—Descriptive Statistics

	1980–2000		1980–2010	
	Mean (1)	SD (2)	Mean (3)	SD (4)
Panel A. Change in adjusted wage gaps				
Male-female	**−0.115**	**0.110**	**−0.137**	**0.130**
High school dropouts	−0.195	0.107	−0.195	0.130
High school graduates	−0.160	0.057	−0.210	0.065
0–4 *years college*	−0.134	0.058	−0.170	0.068
4 *years college*	−0.090	0.087	−0.097	0.105
Advanced degree	0.003	0.107	−0.011	0.142
College-high school (HS)	0.170	0.061	0.224	0.073
Panel B. Other descriptive statistics				
ln(college/HS equivalents), 1980	−0.920	0.287		
Adjusted PCs/worker, 2000	0.458	0.071		
Number of metro areas	230		230	

Notes: Raw data sources are the 1980 (Ruggles et al. 2010), 2000 public use 5 percent Censuses of Population, and the 2009–2011 American Community Surveys (the "2010" data, also from Ruggles et al. 2010) for the wage and human capital variables, and 2000 and 2002 surveys by Harte Hanks for PCs per worker, both of which have been collapsed (using sample weights for census variables) to a metropolitan area-average level dataset whose descriptive statistics are shown in this table. Sample used to compute ln (college/high school equivalents) consists of workers age 16–65 with positive potential work experience (age − years of education − 6), hours worked last year, and not residing in group quarters. College and high school equivalents defined as in Card (2009). Wage sample further limited to those who are currently employed, with positive wage earnings but zero business and farm earnings, and not currently enrolled in school. Wage adjusted, separately by gender and education (and year), for a quartic in potential experience, linear returns to education (for high school dropouts, some college, and advanced degree categories), and dummies for foreign-born, black, Hispanic, and being born after 1950. (The latter is also interacted with years education for the same three groups.) PCs per worker are regression adjusted for three-digit industry × employer size dummies.

II. Results

Panel A of Table 2 show OLS and IV estimates of (1), that is, the effect of PC adoption on the adjusted male-female wage differential (1980–2000). Controlling only for education group effects (which by definition make no difference to the point estimates, since the PC use measure does not vary across education groups), shows that the wage gap declined significantly faster in places where PCs were adopted more intensively, as we saw in Figure 3.[16] The coefficient of -0.22 for 1980–2000 says each additional standard deviation increase in PC use (≈ 0.07) is associated with more than a 1.5 percentage point greater decline in the male-female wage differential.

IV estimates with various controls are shown in columns 2–8. These estimates use the log ratio of college to high school equivalent workers in 1980 as an instrument. As panel C of Table 2 (and also panel A of Figure 4) shows, this initial skill mix measure is indeed strongly related to PC adoption in 2000.[17] The IV estimates are no smaller in magnitude and are also significant.

[16] Figure 3 plots the simple average of the five adjusted wage gaps by education.

[17] This is partly due to the fact that skill mix differences across areas are highly persistent: panel D of Figure 4 shows that the same skill ratio in 2000 is tightly linked to the 1980 measure. BDL showed that 1980 education mix was also related to education mix in 1940 and even in 1880.

Table 2—Change in Adjusted Wage Gaps, 1980-2000, versus PCs per Worker

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Change in adjusted male-female wage gap, 1980–2000								
Estimation:	OLS	IV[a]	IV[a]	IV[a]	IV[a]	IV[a]	IV[a]	IV[a]
Adjusted PCs/worker, 2000	−0.224	−0.363	−0.306	−0.397	−0.318	−0.291	−0.463	−0.653
	(0.0469)	(0.0726)	(0.0819)	(0.132)	(0.132)	(0.107)	(0.211)	(0.277)
Root MSE	0.0846	0.0852	0.0843	0.0850	0.0840	0.0830	0.0844	0.0863
R^2	0.410	0.401	0.416	0.408	0.422	0.457	0.440	0.415
Panel B. Change in adjusted college-high school wage gap, 1980–2000								
Estimation:	OLS	IV[a]	IV[a]	IV[a]	IV[a]	IV[a]	IV[a]	IV[a]
Adjusted PCs/worker, 2000	0.112	0.481	0.461	1.051	1.084	0.602	0.697	0.785
	(0.0601)	(0.0992)	(0.127)	(0.245)	(0.263)	(0.159)	(0.289)	(0.349)
Root MSE	0.0608	0.0662	0.0656	0.0831	0.0845	0.0544	0.0563	0.0584
R^2	0.017					0.247	0.197	0.139
Panel C. First stage: Adjusted PCs/worker, 2000, *versus* ln (*college/HS equivalents*), 1980								
Estimation:		OLS	OLS	OLS	OLS	OLS	OLS	OLS
ln (college/high school equivalents), 1980		0.146	0.150	0.124	0.121	0.183	0.129	0.121
		(0.0137)	(0.0161)	(0.0200)	(0.0206)	(0.0213)	(0.0250)	(0.0266)
R^2		0.350	0.375	0.391	0.393	0.610	0.646	0.652
Observations		1,150	1,150	1,150	1,150	1,150	1,150	1,150
Controls								
Education group?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry mix × broad education?	No	No	2 mfg	2 mfg/svc	2 mfg/svc +index	2 mfg/svc +index	2 mfg/svc +index	2 mfg/svc +index
State effects?[b]	No	No	No	No	No	Yes	Yes	Yes
City controls?[c]	No	No	No	No	No	No	Yes	Yes
Female emp rate × broad ed?	No	No	No	No	No	No	No	Yes

Notes: Dependent variable adjusted for individual-level (in panel C, establishment-level) covariates. Wages adjusted, separately by gender and education (and year), for a quartic in potential experience, linear returns to education (for high school dropouts, some college, and advanced degree categories), and dummies for foreign-born, black, Hispanic, and being born after 1950. (The latter is also interacted with years education for the same three groups.) PCs per worker are regression adjusted for 3 digit industry × employer size dummies. Standard errors (in parentheses) calculated to be robust to arbitrary error correlation with metropolitan area (unit of observation = metro area × 5 education groups) and heteroskedasticity.

[a] Estimated by instrumental variables, using 1980 ln (college/HS equivalents) as instrument. See Table B1 in the online Appendix for reduced form.

[b] "Broad education" is defined as four years college or more versus some college or less. The two "mfg" sectors are durable and nondurable manufacturing share, and the two "svc" are professional services and low-skill services (sum of business and repair services; personal services; entertainment and recreation services). The impact of the four sector share variables is allowed to vary by broad education. The "index" represents the predicted change in female employment share (by broad education) based on an area's initial industry mix (employment shares in detailed census industries).

[c] Unemployment rate, ln (labor force), percent foreign-born, percent Mexican-born.

Sources: 1980 and 2000 Census of Population (Ruggles et al. 2010) and Harte-Hanks (for PC data)

Previous research suggests that some of this relationship could be due to differences in industry mix. The decline in blue-collar wages, thought to perhaps account for a quarter of the decline in the male-female wage gap in the 1980s (O'Neill and Polacheck 1993), will have been more of a factor in initially more blue-collar locations. So column 3 adds controls for initial durable and nondurable manufacturing share, both interacted with broad education (some college or less). Consistent with the decline in blue-collar wages partly driving the result, the estimate is smaller in this column. Olivetti and Petrongolo (2011) document that differences in the size of the service sector can account for a substantial portion of cross-country differences in the gender gap, and, importantly, that the effects differ by broad education. So column 4 adds controls for 1980 employment share in two broad service sectors, again interacted with broad education: professional services, and what might be called "low-skill" services. The former contains industries which are important for high-skill women, like health and education, and the latter contains some sectors that are important for low-skill women, like personal services.[18] The addition of these controls, however, does not appear to diminish the relationship between PC adoption and changes in the male-female wage gap. One could go even further and just control for all one-digit industry shares, or even more detailed controls. The results are robust to a full set of one-digit industry share controls, but a challenge in going further is that, with only 230 metro areas, adding detail to the industry mix quickly becomes infeasible.[19] So we developed a parsimonious way of controlling for detailed industry mix: an index which measures the change in the average "womanpower" requirements of the area's detailed industry mix. This index is $\frac{\sum_j \Delta f_{jb} \ell_{jc}}{\sum_j \ell_{jc}}$, where Δf_{jb} represents the change in the female share of total hours worked in industry j (in our entire sample of 230 metropolitan areas) for broad education group b, and ℓ_{jc} is total hours worked in industry j and city c in 1980. Note that this produces two indexes, one for each broad education group.[20] This control is added in column 5. Consistent with it being related to changes in relative "demand" for female labor, this control is strongly negatively related to changes in the male-female wage gap (not shown in table). Nevertheless, the industry mix controls jointly have a modest effect on the relationship.

Regional differences in the extent of gender discrimination might affect our estimates. These are difficult to quantify. To at least capture the effects of state policies that might affect the male-female wage gap, we control in column 6 for state dummies. The coefficient is essentially unaffected by this control, suggesting such policies do not work in the same direction as our results.[21]

Column 7 adds a few other controls that might have a compositional impact. The unemployment rate attempts to capture any differences in sensitivity of male-female wage gaps to the business cycle (e.g., Hoynes, Miller, and Schaller 2012 document gender differences in cyclical sensitivity), and the natural log of the the city's labor force attempts to capture or agglomeration effects. The latter might be an especially relevant control when examining the college-high school wage gap (panel B), as growth in inequality has been shown to have been more rapid in larger cities

[18] The former contains all industries in SIC 800–899, while the latter includes business and repair services, personal services, and entertainment.

[19] Adding controls for employment share in agriculture/mining, construction, transportation/utilties, wholesale, retail, and finance to column 4—each interacted with broad education, results in a coefficient on initial skill of −0.680 with a standard error of 0.278.

[20] To account for productivity differences across education groups within these broad education categories, the change in female share of hours is calculated for college and high school "equivalents" (Card 2009, definition). The college equivalent index is applied to the top two education groups, and the high school equivalent one is applied to the bottom three.

[21] Indeed, male-female wage gaps were (perhaps unexpectedly) highest in 1980 in highly educated markets like San Francisco, Minneapolis, and Boston where it is likely that there was more widespread support for equal treatment of women. The Equal Rights Amendment, for example, was ratified in California, Minnesota, and Massachusetts, among other states in their regions.

(Baum-Snow and Pavan forthcoming). We also wanted to control for changes in skill mix over time, which might affect wage gaps. One major source of skill mix changes in this period comes from the composition and extent of immigration. As immigrants have a strong tendency to cluster into enclaves, initial immigrant density is a strong predictor of arrivals. We control for overall immigrant workforce share and the share of the largest source country, Mexicans, in 1980. The four city-level controls jointly do little to the relationship between the change in the wage gap and PC adoption.[22]

Column 8 controls for female employment rates by broad education. This is a simple attempt to control for selection. Although it is measured in 1980, we recognize that this control is still potentially endogenous, so we added it last. However, it gives little indication that selection is driving our results. A more thorough analysis of selection issues appears in the online Appendix and is summarized in the robustness section.

Panel B shows that there is, as has been previously documented (BDL), a strong positive relationship between the change in the college-high school wage gap and PC adoption. The IV coefficient, which varies from around 0.5 to 1, says that a 1 standard deviation increase in PC adoption is associated with a more than 3 percentage point increase in the college-high school wage gap between 1980 and 2000. In this case, the OLS estimates are considerably smaller than the IV estimates. As BDL discussed, this is likely because any third factors that make college educated labor relatively expensive would tend to diminish PC adoption.

Table 3 shows results extending the final year to 2010, using ACS data. We lack a PC use measure for 2010, so here we only show the reduced form relationship between changes in wage gaps and 1980 skill mix, our instrument. By way of comparison, the reduced form for 1980–2000 is shown in the online Appendix, Table B-1. The effects are somewhat larger to 2010, consistent with some continuing effect of technological change. These estimates are also less sensitive to controls. It is possible that the other influences that affect the relationship to 2000 are mainly concentrated in the 1980s, such as the decline in blue-collar wages, making the longer difference less sensitive to controls.

A. *What Do the Cross-Sectional Results Imply for the Aggregate* (*Time Series*) *Decline in the Wage Gap?*

So far we have shown that the change in the male-female wage gap and the change in the college-high school wage gap have opposite signed relationships with PC use (or 1980 education levels), consistent with a two-skill model of workers in which the price of the cognitive (or interpersonal) skill relative to manual skills has been raised by the introduction of PCs. Now we would like to use our estimates to examine how much of the decline in the national level male-female wage gap in the past few decades can be attributed to changing skill prices.

[22] Adding controls for black and Hispanic share also has little impact on the estimates. Recall that wages are already adjusted at the individual level for race, ethnicity, and immigrant status. A direct control for the change in ln(college/high school equivalents) is not significant and does not affect the point estimate on initial skill mix.

Table 3—Change in Adjusted Wage Gaps, 1980–2010, versus ln (College/HS Equivalents), 1980

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Change in adjusted male-female wage gap, 1980–2010							
ln (college/high school equivalents), 1980	−0.0578	−0.0611	−0.0570	−0.0534	−0.0649	−0.0597	−0.0697
	(0.0141)	(0.0164)	(0.0197)	(0.0193)	(0.0225)	(0.0270)	(0.0296)
R^2	0.342	0.365	0.368	0.377	0.413	0.414	0.415
Panel B. Change in adjusted college-high school wage gap, 1980–2010							
ln(college/high school equivalents), 1980	0.123	0.138	0.199	0.197	0.196	0.175	0.184
	(0.0149)	(0.0182)	(0.0213)	(0.0216)	(0.0277)	(0.0353)	(0.0360)
R^2	0.234	0.269	0.319	0.331	0.526	0.540	0.542
Observations	1,150	1,150	1,150	1,150	1,150	1,150	1,150
Controls							
Education group?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry mix × broad education?[a]	No	2 mfg	2 mfg/svc	2 mfg/svc +index	2 mfg/svc +index	2 mfg/svc +index	2 mfg/svc +index
State effects?	No	No	No	No	Yes	Yes	Yes
City controls?[b]	No	No	No	No	No	Yes	Yes
F emp rate × broad ed?	No	No	No	No	No	No	Yes

Notes: Wages adjusted, separately by gender and education (and year), for a quartic in potential experience, linear returns to education (for high school dropouts, some college, and advanced degree categories), and dummies for foreign-born, black, Hispanic, and being born after 1950. (The latter is also interacted with years education for the same three groups.) Standard errors (in parentheses) calculated to be robust to arbitrary error correlation with metropolitan area (unit of observation = metro area × 5 education groups) and heteroskedasticity.

[a] "Broad education" is defined as four years college or more versus some college or less. The two "mfg" sectors are durable and nondurable manufacturing share, and the two "svc" are professional services and low-skill services (sum of business and repair services; personal services; entertainment and recreation services). The impact of the four sector share variables is allowed to vary by broad education. The "index" represents the predicted change in female employment share (by broad education) based on an area's initial industry mix (employment shares in detailed census industries).

[b] Unemployment rate, ln (labor force), percent foreign-born, percent Mexican-born.

Sources: 1980 Census of Population and stacked 2009–2011 American Community Surveys (Ruggles et al. 2010); the latter are the "2010" data

One way to do this is to look at the coefficient on PC adoption, and apply to it the average PCs per worker nationally (in 2000). One needs to be careful with this totally different source of variation: the increase in PC use nationally was presumably driven by a fall in PC prices, whereas the variation across labor markets we use to estimate its impact holds constant the price of PCs. That said, it turns out the magnitude is about what it needs to be to explain most of the decline in the male-female wage gap over this period. That is, multiplying the coefficient, ≈ -0.3, with average PC use, 0.46 (Table 1), we predict a fall in the male-female wage gap by the year 2000 of ≈ 0.138; the actual decline was 0.115.

In the online Appendix, we argue that the following approach is theoretically better. The idea is to use the conditional correlation between the gender and education wage gaps implied by the ratio of either our IV estimates (in panels A and B of Table 2) or by our reduced form estimates (Table 3) to calculate a contribution. The ratio of these estimates tell us how much the gender wage gap should move for a 1 percent change in the college-high school gap if the later is driven by changes in the returns to skill prices. If we are willing to assume that most of the national-level (time series) increase in the college-high school wage gap is due over this period to the adoption of IT, then we can simply multiply the observed increase over time in the college-high school wage gap by the ratio of our estimates to get the implied contribution of IT diffusion to the national level decline in the male-female wage gap.

The ratio of our estimated responses of wage gaps to PC adoption in Table 2 range from −0.3 to −0.75. Alternatively, using the 1980–2010 reduced forms coefficients from Table 3, produces implied relationships between male-female and college-high school wage gaps that range from −0.3 to −0.45. If we now multiply these ranges with the national-level increase in the college-high school wage gap (Table 1) we see that the process can account from 44 percent to 111 percent of the observed decrease in the male-female wage gap 1980 to 2000, and 49 percent to 74 percent of the observed decrease 1980 to 2010, which is very substantive.

III. Robustness Checks

In order to save space, we merely summarize a number of robustness checks we have attempted, with details confined to an online Appendix. These robustness checks ask: (i) To what extent are our estimates driven by changes in the selection of women into the labor force? (ii) To what extent are the estimates driven by the cohort composition of women? And, (iii) does the timing of wage changes match the timing of the arrival of PCs, or did similar changes in wage structure occur before the arrival of PCs?

Selection is an important alternative explanation for the coincident timing of the aggregate trends in Figure 1 raised by Mulligan and Rubinstein (2008) (MR), and a similar logic could apply at the city level; increases in the return to skill could induce higher skill women to enter the workforce. In fact, we find little sign that this is what drives the relationship in Tables 2 and 3. Online Appendix Table B-2 shows the pattern of wage changes are similar for women without and with young kids (the former are largely responsible for the increase in positive selection in MR's story), and online Appendix Table B-3 shows that the increase in female employment rates is uncorrelated with initial skill mix. There also continues to be a negative relationship between initial skill mix and changes in male-female wage gaps conditional on a MR-style parametric selection control (online Appendix Table B-2).[23]

A second reason the magnitude of our estimates could be overstated is that areas that were initially more educated tend to have younger workforces, and the greater labor force attachment of younger cohorts—perhaps induced by the availability of new birth control technology—may have contributed to a decline in the male-female wage gap (Bailey, Hershblein, and Miller 2012). In online Appendix Table B-4 we find, however, that male-female wage gaps negatively covary with initial skill mix within most of the birth cohorts that it is possible to observe in both 1980 and 2010. That said, like previous studies, we find that the *mean* change in wage gaps within cohort is near zero—almost all of the decline is across cohorts—consistent with greater labor force attachment explaining some of the decline in the aggregate.

[23] Our results are therefore consistent with Machado (2013) and Herrmann and Machado's (2012) argument that MR's results overstate the role of selection in accounting for the decline in the gender wage gap.

Finally, if changes in wage gap prior to the 1980s were also correlated with skill mix, it would weaken the argument that this was driven by IT diffusion. In fact, in online Appendix Table B-5 we find that the correlation between skill mix and changes in wage gaps is not present in the 1970s.

IV. Conclusion

Motivated by the simultaneous decline in male-female and rise in education wage gaps in recent decades, this paper has asked whether both trends may have been driven by changes in the relative price of skill attributes induced by the diffusion of information technology. In particular, if both women and educated workers embody an abundant supply of "cognitive" skills relative to manual skills—which appears to be the case in task data—and if information technology is relatively cognitive-augmenting, then we should expect male-female wage gaps and returns to education to co-move negatively in response to PC adoption. This idea has been suggested before. The aim of this paper has been to go beyond the time series evidence and instead explore cross-city patterns with the recognition that technological diffusion is an endogenous process.

Consistent with the idea that females' relative wages have risen because of their comparative advantage in cognitive tasks, we find that markets that adopted PCs more intensively experienced faster decreases in the male-female wage gap. This relationship remains strong when controlling for industry mix, and when examining the relation between wage gaps and PC adoption rates predicted from level of educational attainment present in a locality prior to the arrival of PCs.

Our estimates survive attempts to account for cross-city differences in the selection of women in the workforce, including focusing on female subgroups with high propensities to work, as well as controlling for an estimate of the selection bias. Overall, our estimates are consistent with changing skill prices accounting for more than 50 percent of the decline in the male-female wage gap 1980–2000.[24]

REFERENCES

Autor, David H., Frank Levy, and Richard J. Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *Quarterly Journal of Economics* 118 (4): 1279–1333.

Bacolod, Marigee P., and Bernardo S. Blum. 2010. "Two Sides of the Same Coin: U.S. 'Residual' Inequality and the Gender Gap." *Journal of Human Resources* 45 (1): 197–242.

Bailey, Martha J., Brad Hershbein, and Amalia R. Miller. 2012. "The Opt-In Revolution? Contraception and the Gender Gap in Wages." *American Economic Journal: Applied Economics* 4 (3): 225–54.

Baum-Snow, Nathaniel, and Ronni Pavan. Forthcoming. "Inequality and City Size." *Review of Economics and Statistics*.

Beaudry, Paul, Mark Doms, and Ethan Lewis. 2010. "Should the Personal Computer Be Considered a Technological Revolution? Evidence from U.S. Metropolitan Areas." *Journal of Political Economy* 118 (5): 988–1036.

[24] This does not mean that other forces have not influenced gender equality in earnings. For example, our estimates are consistent with a nontrivial role for increased labor force attachment of newer cohorts of women. Our estimates are also adjusted for individual characteristics, which may partly or entirely reflect choices made in response to changes in labor market opportunities driven by other forces.

Beaudry, Paul, and David Green. 2003. "Wages and Employment in the United States and Germany: What Explains the Differences?" *American Economic Review* 93 (3): 573–602.

Beaudry, Paul, and David A. Green. 2005. "Changes in U.S. Wages, 1976–2000: Ongoing Skill Bias or Major Technological Change?" *Journal of Labor Economics* 23 (3): 609–48.

Beaudry, Paul, David A. Green, and Benjamin M. Sand. 2013. "Spatial Equilibrium with Unemployment and Wage Bargaining: Theory and Estimation." National Bureau of Economic Research (NBER) Working Paper 19118.

Beaudry, Paul, and Ethan Lewis. 2014. "Do Male-Female Wage Differentials Reflect Differences in the Return to Skill? Cross-City Evidence from 1980–2000: Dataset." *American Economic Journal: Applied Economics*. http://dx.doi.org/10.1257/app.6.2.178.

Black, Dan, Natalia Kolesnikova, and Lowell Taylor. 2009. "Earnings Functions When Wages and Prices Vary by Location." *Journal of Labor Economics* 27 (1): 21–47.

Black, Sandra E., and Alexandra Spitz-Oener. 2010. "Explaining Women's Success: Technological Change and the Skill Content of Women's Work." *Review of Economics and Statistics* 92 (1): 187–94.

Blanchard, Olivier Jean, and Lawrence F. Katz. 1992. "Regional Evolutions." *Brookings Papers on Economic Activity* 1: 1–61.

Blau, Francine D., and Lawrence M. Kahn. 1997. "Swimming Upstream: Trends in the Gender Wage Differential in the 1980s." *Journal of Labor Economics* 15 (1, Pt.1): 1–42.

Blau, Francine D., and Lawrence M. Kahn. 2006. "The U.S. Gender Pay Gap in the 1990s: Slowing Convergence." *Industrial and Labor Relations Review* 60 (1): 45–66.

Card, David. 2009. "Immigration and Inequality." *American Economic Review* 99 (2): 1–21.

Card, David, and John E. DiNardo. 2002. "Skill-Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles." *Journal of Labor Economics* 20 (4): 733–83.

Caselli, Francesco. 1999. "Technological Revolutions." *American Economic Review* 89 (1): 78–102.

Caselli, Francesco, and Wilbur John Coleman, II. 2001. "Cross-Country Technology Diffusion: The Case of Computers." *American Economic Review* 91 (2): 328–35.

Doms, Mark, and Ethan Lewis. 2006. "Labor Supply and Personal Computer Adoption." Federal Reserve Bank of San Francisco Working Paper 2006-18.

Fortin, Nicole M., and Thomas Lemieux. 2000. "Are Women's Wage Gains Men's Losses? A Distributional Test." *American Economic Review* 90 (2): 456–60.

Goldin, Claudia. 1990. *Understanding the Gender Gap: An Economic History of American Woman.* New York: Oxford University Press.

Goldin, Claudia, and Lawrence F. Katz. 2002. "The Power of the Pill: Oral Contraceptives and Women's Career and Marriage Decisions." *Journal of Political Economy* 110 (4): 730–70.

Goldin, Claudia, and Lawrence F. Katz. 2008. *The Race Between Education and Technology*. Cambridge: Harvard University Press.

Herrmann, Mariesa, and Cecilia Machado. 2012. "Patterns of Selection in Labor Market Participation." https://docs.google.com/file/d/0B-DH4T6okuytOVhMMXhkbFFJSWc/edit.

Hoynes, Hilary, Douglas L. Miller, and Jessamyn Schaller. 2012. "Who Suffers during Recessions?" *Journal of Economic Perspectives* 26 (3): 27–48.

Lemieux, Thomas. 2006. "The 'Mincer Equation' Thirty Years after Schooling, Experience, and Earnings." In *Jacob Mincer: A Pioneer of Modern Labor Economics*, edited by Shoshana Grossbard, 127–48. New York: Springer Verlag.

Machado, Cecilia. 2013. "Selection, Heterogeneity and the Gender Wage Gap." https://docs.google.com/file/d/0B-DH4T6okuytUm1EVTlTakxrMW8/edit.

Mincer, Jacob, and Solomon Polachek. 1974. "Family Investments in Human Capital: Earnings of Women." *Journal of Political Economy* 82 (2, Pt. 2): S76–108.

Mulligan, Casey B., and Yona Rubinstein. 2008. "Selection, Investment, and Women's Relative Wages Over Time." *Quarterly Journal of Economics* 123 (3): 1061–1110.

National Academy of Sciences, Committee on Occupational Classification and Analysis. 2009. "Dictionary of Occupational Titles (DOT): Part I - Current Population Survey, April 1971, Augmented with DOT Characteristics." [Computer File]. ICPSR07845-v2. Washington, DC: U.S. Department of Commerce, Bureau of the Census [producer], 1981. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor].

Neal, Derek. 2004. "The Measured Black-White Wage Gap among Women Is Too Small." *Journal of Political Economy* 112 (Supplement 1): S1–28.

Olivetti, Claudia, and Barbara Petrongolo. 2011. "Gender Gaps across Countries and Skills: Supply, Demand and the Industry Structure." National Bureau of Economic Research (NBER) Working Paper 17349.

O'Neill, June, and Solomon Polachek. 1993. "Why the Gender Gap in Wages Narrowed in the 1980s." *Journal of Labor Economics* 11 (1): 205–28.

Ruggles, Steven, J. Trent Alexander, Katie Genadek, Ronald Goeken, Matthew B. Schroeder, and Matthew Sobek. 2010. Integrated Public Use Microdata Series: Version 5.0 [Machine-readable database]. Minneapolis: University of Minnesota.

Weinberg, Bruce A. 2000. "Computer Use and the Demand for Female Workers." *Industrial and Labor Relations Review* 53 (2): 290–308.

Welch, Finis. 2000. "Growth in Women's Relative Wages and in Inequality among Men: One Phenomenon or Two?" *American Economic Review* 90 (2): 444–49.

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