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

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August 2012

Abstract

Over the 1980s and 1990s the wage differentials between men and women declined significantly while returns to education increased. We ask if this reflects a change in the relative price of skills which are more abundant in both women and more educated workers. In parallel to the aggregate pattern, we find male-female and education wage differentials moved in opposite directions 1980-2000 across metropolitan areas. Our estimates are larger when we isolate variation mostly likely driven by technological change, and imply most of the decline in the male-female wage differential 1980-2000 was driven by changes in the relative price of skills.

*The authors acknowledge the helpful comments of seminar participants at the NBER Summer Institute, McMaster University, University of British Columbia, the Federal Reserve Bank of San Francisco, Queens College, and Dartmouth College. Mark Doms was heavily involved in the early stages of this project, and we are indebted to him for his substantial input. All errors are our own.

Over the 1980-2000 period the US wage gap between men and women with similar characteristics decreased significantly. Since 2000 this wage gap has stayed quite stable.[1] There are many proposed explanations for the observed decrease in the gender wage gap, including increased positive selection of women into the labor market (Mulligan and Rubinstein, 2008), an improved match between actual and potential measures of experience due to their greater labor force attachment (O'Neill and Polacheck, 1993; Bailey, Hershblein, and Miller, 2012) – and decreased discrimination.[2] One especially intriguing observation is that the gender wage gap has mirrored rather closely movements in the return to education over this period (see Figure 1), with the gender gap decreasing when the return to education increased.[3] This has had lead some researchers, most notably Welch (2000), to conjecture that the two patterns may be driven by a common underlying force.[4] According to this conjecture, men and women (with similar education) bring to the market different bundles of skills, as do more educated relative to less educated individuals. When methods of production change drastically – such as with the introduction and diffusion of the PC – this changes the price of different skill attributes which in turn induces movements in the gender wage gap and education wage gaps, since both gaps compare the value of skill bundles. To be more precise, if individuals are viewed as bringing to the market both soft-cognitive skills (or interpersonal skills) and hard-motor skills (or brawn), and if women and more educated workers are both relatively

[1]It is also quite stable prior to 1980 (O'Neill and Polacheck, 1993).

[2]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.

[3]The regression of the gender wage gaps in Figure 1 on the college-high school wage gap gives -0.625 for the high school level gender gap and -0.787 for the college level gender gap.

[4]Another view was that rising wage gaps 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 which we pursue in this paper. Blau and Kahn did note in their paper that the higher rate of computer use among women than men suggested women may have actually relatively benefitted from, rather than been harmed from, skill-biased technological change.

more endowed is such softer skills, then an increase in the relative price of soft versus hard skills should cause the male-female wage gap to decrease at the same time as the return to education increases. While some evidence lends support to this view, the literature on gender gaps appears to remain skeptical of its relative importance in explaining the decrease in the wage gap observed over the 1980s and 1990s, since the claim is backed-up foremost by time-series evidence (which could easily be spurious) or else does not directly analyze gender wage gaps.[5] The object of this paper is to more thoroughly flesh out the empirical content of this conjecture and then explore its implications for cross-city observations on gender gaps and returns to education.

The idea that a change in the relative price of soft/cognitive skills versus hard/motor skills could be behind some or all of the decrease in the gender wage gap observed over the 1980-2000 period is a rather straightforward proposition. However, empirically evaluating its relevance is hindered by the fact that the relevant relative price is not directly observable. As we will show using a simple two attribute model, when female workers and more educated workers have relatively more soft-cognitive versus hard-motor skills than other types of workers, then the relative price of soft versus hard skills plays the role of a common latent factor that drives in opposite directions the gender gap and the return to education. The main idea of this paper is to examine the quantitative relevance of this unobserved factor by examining how city level measures of the gender gap and the return to education change in response to forces that likely caused changes in the local price of these skills. If this common factor is present, then the gender gap and the return to education should systematically co-move in opposite directions in response to forces that affect the relative price of soft versus

[5]The evidence in support of this view includes the time series correlation between the male-female wage gap and the returns to education (such as in Figure 1; also Welch, 2000, and Fortin and Lemieux, 2000) the decline in wages in jobs which require motor skills and the rise in wages in jobs which require cognitive skills (Bacolod and Blum, 2010), and the correlation across industries between the change in female employment share and the adoption of computers, especially in blue collar jobs (Weinberg, 2000). Black and Spitz-Oener's (2010) finding 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 was associated with computerization) is also consistent with the decline in the wage gap having a technological origin.

hard skills.

The main challenge in implementing this simple idea is finding city level factors that plausibly affect city level relative prices of skill.[6] To make headway in identifying such factors, we refer to the capital-skill complementarity literature which argues that 1980 to 2000 was a period where the introduction of new capital equipment – most notably the PC – drastically changed the relative price of certain skills since it acted as a substitute for many motor or hard skills, and a complement for more cognitive skills.[7] Based on this view, one may consider regressing city level observations of both changes in gender wage gaps and in returns to education on measures of technological adoption — such as the local use of PCs – and see if these two wage differentials move in opposite directions. While we will report the results of such an exercise, such an approach is potentially problematic as technological adoption is itself an endogenous process. For this reason, we also use insight from the endogenous technological adoption literature (similar to that used in Beaudry, Doms & Lewis, 2010) to illustrate how local labor market conditions prior to the introduction of the PC can be used as instruments for technology adoption. The main idea is that, if PCs complement soft skills and substitute for hard skills, then they should be adopted most strongly in localities where soft skills were initially relatively abundant. Hence this idea suggests that the city level change in the gender wage gap and the return to education should respond in opposite directions to measures of a city's pre-PC-era relative abundance of these skills.

Using data from the 1980 and 2000 Censuses of Population, we begin by examining whether the gender wage gap and the return to education moved in opposite directions across cities

[6]To identify the relevant co-movement, these factors must simultaneously be uncorrelated with other residual factors which may affect either the gender wage gap or the returns to skill.

[7]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 is therefore depends on comparative advantage: the relative price of (and therefore supply of) skill. This is empirically supported in Beaudry and Green, 2003, 2005; and Beaudry, Doms, and Lewis, 2010. Autor, Levy and Murnane (2003) also model computer adoption as responding to skill ratios, and a version of their model will be the main model of production we consider in this paper. Another view is that PCs are the latest example of ongoing improvements in the quality of capital that favor skilled workers which perhaps goes back as much as a century (Goldin and Katz, 2008).

during this period. Interestingly, we find that the cross-city evidence echoes the time series pattern of strong negative co-movement, thereby providing initial evidence supporting the conjecture that the gender wage gap and the return to education may be driven by a common latent force. However, based on OLS estimates, the cross-city co-movement is substantially weaker than that found in the time series. We then exploit the insights of the endogenous technological adoption literature in the presence of capital skill complementarity to explore instrumental variable estimates of this relationship. Again, this class of models suggest that cities where soft skills were most abundant "pre-PC" (in 1980) should be the same cities where PCs are adopted most rapidly, inducing a greater increase in the return to education and a greater decrease in the gender gap. We report evidence in support of each element of this process. Our main finding is that, once we isolate variation in the wage data more likely driven by changes in the relative prices of unobserved skills, we find that the cross-city link between gender wage gap and the return to education to be very similar to that found in the time series. We then use the cross-city evidence to help answer our initial time series question. Our results suggest that most of the aggregate reduction in the male female wage differential observed during the 1980-2000 period can be attributed to the change in a latent relative price of a skill which is more abundant in both female and more educated workers.

The remaining sections of the paper are structured as follows. In the next section we present the simple theoretical structure which guides our approach to the data. The theory encompasses two elements: first, we clarify how gender gaps and returns to education are related in a two attribute model of wage through a common latent factor. Then we use insights from the literature on capital-skill complementarity and endogenous technological adoption to discuss the identification of the effects of the common latent factor. Section 2 presents the data used to examine determinants of the gender wage gaps and discusses implementation and identification issues. Section 3 presents our main results, and Section 4 presents robustness checks. In the empirical analysis, we examine in depth issues of selection that may bias our results, as such issues are thought to be potentially very important in the behavior of the gender wage gap over our period of interest (Mulligan and Rubinstein, 2008). Section 5 discusses the implication of the estimates for aggregate changes. Section 6 concludes.

1 Theory

The idea we want to evaluate is whether changes in the gender wage gap and in the return to education may be driven by a common underlying force reflecting the price of a skill which is relatively more abundant among women and more educated workers. In particular, the main hypothesis is that the role of this common factor driving the gender wage gap became most evident during the 1980-2000 period when technological change – as reflected in the diffusion of PCs– considerably changed relative prices of skills. The object of this section is to present a simple theoretical structure which will clarify how we can use cross-city variation in wage outcomes to examine the issue. As noted in the introduction, there are two distinct components which underly the theory. On the one hand, there is the notion that wages reflect payments to bundles of skills. On the other hand, there is the idea that the diffusion of PCs tended to increase the relative price of cognitive-soft skills because of its complementarity to such factors, while it acts as a substitute for more routine-hard skills. We now present each of these elements in turn in order to derive estimating equations and associated instrumental variable strategies.

1.1 The gender wage gap and the returns to education in a two attribute model

To begin, consider an environment where each worker brings to the market a two dimensional vector of skills. The two components will be referred to as cognitive-soft skill (denoted S) and raw labor (denoted L). Individuals differ in the amount of each skill they possess. Let γ_{eg}^{S} represent the amount of cognitive skill embodied in a a worker with education $e \in \{e_1, e_2, ..., e_N\}$ and gender $g \in \{m, f\}$, and let γ_{eg}^{L} represent the amount of raw labor embodied in the same individual. For an individual in city c at time t his wage will be given by

$$(1) \quad W_{egct} = (\gamma_{eg}^{S} w_{ct}^{S} + \gamma_{eg}^{L} w_{ct}^{L})\eta_{egct},$$

where w_{ct}^S and w_{ct}^L are the local prices of the cognitive skill and of raw labor respectively at time t, and η_{egct} combines any systematic discrimination θ_{egt} (that can potentially vary over time by gender and education) and a pure measurement error term ν_{egct} ($\eta_{egct} = \theta_{egt} + \nu_{egct}$). For now, we need not focus on why people with different skills may cluster more in some locations than others. Instead, we can take the cross-city distribution of worker types as given and postpone a discussion of the related endogeneity issues.

The main difficulty with using equation (1) is that none of the right hand side terms are directly observable. Nonetheless, we can pursue some of its empirical implications by examining wage gaps across individuals. We begin with the male-female log wage gap at education level e, which we denote $MFdiff_{ect}$. From (1), this can be expressed as

$$\begin{aligned} MFdiff_{ect} &= \ln W_{emct} - \ln W_{efct} \\ &= \ln \frac{\gamma_{em}^L}{\gamma_{ef}^L} + \ln\left(1 + \frac{\gamma_{em}^S}{\gamma_{em}^L}\frac{w_{ct}^S}{w_{ct}^L}\right) - \ln\left(1 + \frac{\gamma_{ef}^S}{\gamma_{ef}^L}\frac{w_{ct}^S}{w_{ct}^L}\right) + \ln\eta_{emct} - \ln\eta_{efct} \\ &\approx \ln \frac{\gamma_{em}^L}{\gamma_{ef}^L} + \left(\frac{\gamma_{em}^S}{\gamma_{em}^L} - \frac{\gamma_{ef}^S}{\gamma_{ef}^L}\right)\frac{w_{ct}^S}{w_{ct}^L} + \ln\eta_{emct} - \ln\eta_{efct}, \end{aligned}$$

or, to simplify the notation, we can express it as:

$$(2) \qquad MFdiff_{ect} \approx \alpha_e^1 + \beta_e^1 P_{ct}^S + \varepsilon_{ect},$$

where $\alpha_e^1 = \ln \frac{\gamma_{em}^L}{\gamma_{ef}^L}$, $\beta_e^1 = \frac{\gamma_{em}^S}{\gamma_{em}^L} - \frac{\gamma_{ef}^S}{\gamma_{ef}^L}$, $P_{ct}^S = \frac{w_{ct}^S}{w_{ct}^L}$, and $\varepsilon_{ect} = \ln\eta_{emct} - \ln\eta_{efct}$. Equation (2) says that the cross-city differences in the male-female wage gap depend on a common education group effect and varies across cities because of differences in the relative price of skills, P_{ct}^S. Similarly, the within gender wage gap between education levels e_j and e_i, denoted $E_{ji}diff_{gct}$, can also be expressed as a function of the relative price of skills.

$$\begin{aligned} (3) \qquad E_{ji}diff_{gct} &= \ln W_{e_jgct} - \ln W_{e_igct} \\ &\approx \alpha_{jig}^2 + \beta_{jig}^2 P_{ct}^S + \varepsilon_{e_jigct} \end{aligned}$$

with $\alpha^2_{jig} = \ln \frac{\gamma^L_{e_j g}}{\gamma^L_{e_i g}}$ and $\beta^2_{jig} = \frac{\gamma^S_{e_j g}}{\gamma^L_{e_j g}} - \frac{\gamma^S_{e_i g}}{\gamma^L_{e_i g}}$ and $\varepsilon_{e_{ij}gct} = \ln \eta_{e_i gct} - \ln \eta_{e_j gct}$.

Equations (2) and (3) illustrate that in a two attribute model, both the gender wage gap and the returns to education are linked by the relative price of skills which acts as a latent common factor. Moreover, if we are willing to assume that at a given level of education men have a smaller ratio of soft skills to raw labor (which implies $\beta^1_e < 0$) and that within gender more educated workers have have relatively more soft skills (so if $e_j > e_i$, then $\beta^2_{jig} > 0$), then we see that change in the relative price of skills P^S will cause the gender wage gap and the returns to education to move in opposite directions.

Although (3) and (2) still cannot be directly estimated, part of what we will exploit in estimation is changes in the prices of skills during the era of PC diffusion. So taking differences of (3) and (2) we get:

$$(4) \qquad \Delta MFdiff_{ec} \approx \beta^1_e \Delta P^S_c + \Delta\varepsilon_{ec}$$

$$(5) \qquad \Delta E_{ji} diff_{gc} \approx \beta^2_{jig} \Delta P^S_c + \Delta\varepsilon_{e_{ji}gc}$$

Note that the error terms in (5) and (4) may not have a zero mean as they potentially contain changes in systematic discrimination (changes in θ_{egt}). If we substitue (5) into (4) to eliminate the unobserved skill price, we get the following relation between the gender wage gap and the returns to education:

$$(6) \qquad \Delta MFdiff_{gec} \approx \frac{\beta^1_e}{\beta^2_{jig}} \Delta E_{ji} Diff_{gc} + \Delta\varepsilon_{ec} - \frac{\beta^1_e}{\beta^2_{jig}} \Delta\varepsilon_{e_{ji}gc}$$

Our conjectures about skill endowments imply $\beta^1_e/\beta^2_{jig} < 0$. [8] One of our main goals will be to estimate (6) consistently, as this will be necessary to help evaluate the role of changes in skill price for explaining aggregate changes in the gender wage gap. However, even leaving aside the potential endogeneity of cross-city wage variation in (6), the fact that wage gaps are likely measured with error implies OLS estimates of β^1_e/β^2_{jig} will be substantially attenuated.

[8] β^1_e/β^2_{jig} may vary across education groups but we will restrict it to be constant in our estimation.

In order to estimate (6) consistently, we will therefore need instruments for the returns to education that reflect changes in the relative price of skill ΔP^S. For this reason, we now discuss how we can use insights from the capital-skill complementarity literature to find such instruments.

1.2 Production and Endogenous PC Adoption

In order to discuss factors determining the relative price of skills, consider an environment where there is only one produced good and where prices reflect marginal products. Initially, the good is produced using only the skills of different workers. Then we consider the introduction of a new capital good which is meant to capture the introduction of PC's. Our aim is to highlight how this affects the price of the two different skill attributes. For expositional simplicity, we follow Autor, Levy , and Murnane (2003) (hereafter, ALM) and model the economy after the arrival of computing technology with the following Cobb-Douglass production structure:

$$(7) \quad Q_c = A\left(\mu_c^{PC} PC_c + L_c\right)^{\alpha} S_c^{1-\alpha}$$

where Q_c represents aggregate output, L_c is the aggregate level of raw labor supplied by the different individuals hired in market c, S_c represents the aggregate amount of soft skilled hired in market c, PC_c represents the use of personal computers, and $\alpha \in (0, 1)$. The only way in which this production function differs from ALM is the factor loading μ_c^{PC}, which we include to capture potential city-specific productivity differences in the use of PCs.[9] The important element of this technology is that PCs substitute for raw labor and complement the soft-cognitive skill. The results we exploit in what follows relies on this assumption but not on the particularly restrictive functional form given by 7.[10]

Now, consider a period before the arrival of PCs, which we will call $t = 1980$ to match our empirics below. We model this by setting $\mu_c^{PC} = 0$, so $Q_c = AL_c^{\alpha} S_c^{1-\alpha}$. This implies that

[9] In ALM, this production function represented many industries, each with different αs.

[10] See Beaudry, Doms and Lewis (2010) for a more general discussion.

before the arrival of PCs, the relative price of soft skills versus raw labor is given by:

$$(8) \qquad P^S_{c,1980} = \ln \frac{w^S_{c,1980}}{w^L_{c,1980}} = \ln \frac{1-\alpha}{\alpha} - \ln \left(\frac{S_{c,1980}}{L_{c,1980}} \right) = \ln \frac{1-\alpha}{\alpha} - \ln s_{c,1980}$$

where $s_{c,1980} = \frac{S_{c,1980}}{L_{c,1980}}$. Equation (8) simply indicates that the relative price of soft skills prior to the introduction of PCs was negatively related to the local abundance of soft skills.[11] After the arrival of the PC, which we assume is available in all localities at the same price (denoted P^{PC}), we can express the change in the relative price of skills in two different manners depending on whether or not we use the optimally condition for the determination of PCs which is given by:

$$\ln \left(\alpha \mu_c^{PC} A \right) - (1-\alpha) \ln \left(\mu_c^{PC} \frac{PC_c}{L_c} + 1 \right) + (1-\alpha) \ln s_c = \ln P^{PC}$$

If we use this optimality condition in conjunction with the marginal product conditions for each skill, we can express the change in the price of skill as:

$$(9) \qquad \Delta \ln P^S_c = \frac{\ln (\alpha A) - \ln P^{PC}}{1-\alpha} + \ln s_{c,1980} + \frac{\ln \left(\mu_c^{PC} \right)}{1-\alpha}$$

Equation (9) indicates that the change in the relative price of skill at the city level will be greatest where its relative supply is initially most abundant (i.e. where $s_{c,1980}$ is greatest). This property reflects the capital-skill complementary of the arrival of the PC.[12] Before the arrive of the PC, regions with more soft-cognitive skills have a relatively low price for this skill and a high price for hard skills. This makes the adoption of PCs very attractive in such a market. Therefore, PCs should be adopted more aggressively in such market causing the relative price of soft skill to increase most where soft skills are initially more abundant. If we use (9) to replace ΔP^S in 4 and 5 we get

$$(10) \quad \Delta MFdiff_{ec} = \beta^1_e \frac{\ln (\alpha A) - \ln P^{PC}}{1-\alpha} + \beta^1_e \ln s_{c,1980} + \beta^1_e \frac{\ln \left(\mu_c^{PC} \right)}{1-\alpha} + \Delta \varepsilon_{ec}$$

[11] This property holds for a wide variety of production setups and we can easily generalize the structure as not to obtain a unit elasticity.

[12] This property does not rely on the particular functional form of the production function but does depends on the arrival a new technology where the PC is a complement to soft skills and a substitute to hard skills.

$$\text{(11)} \quad \Delta E_{ji}diff_{gc} = \beta_{jig}^{2}\frac{\ln(\alpha A) - \ln P^{PC}}{1-\alpha} + \beta_{jig}^{2}\ln s_{c,1980} + \beta_{jig}^{2}\frac{\ln\left(\mu_c^{PC}\right)}{1-\alpha} + \Delta\varepsilon_{e_{ji}gc}$$

The interesting aspect of these two equations is that they now contrast how cross-city movements in the gender wage gap and the returns to education will respond differently to a potentially observable aggregate factor: the relative supply of skills. In particular, these equations indicate that following the introduction of the PCs, we should see the gender wage gap fall most in cities where soft skill were most abundant prior to the arrival to the PC (since, again, $\beta_e^1 < 0$). Moreover, it indicates that we should simultaneously see the greatest increase in the return to education precisely in these same cities. If we have a measure of these relative skills, then in principle we can estimate (10) and (11) consistently by OLS under the assumption that the local skill supply prior to the arrival of PC was not anticipating which cities would be best at using PCs (ie, the skill supply in 1980 is not systematically related to μ_c^{PC}). These two equations also suggest that one way of estimating equation (6) is to use measured skills in 1980 as an instrument for $\Delta ED_{ij}diff_c$. This should also allow for consistent estimates under the assumption that skill supply in 1980 did not forecast PC efficiency across cities.

While equation (9) offers a simple and useful way of linking changes in the relative price of skill and initial skill supplies, it hides much of the mechanism underlying the the model. In particular, by using the optimality condition for the adoption of PCs, we have somewhat obscured the fact that it is the adoption of the new technology that, according to the capital-skill complementarity view, is causing the opposite movements in the gender wage gap and the returns to education. In order to see these intermediate forces more explicitly, it is useful to express the change the relative price of skill using only marginal product conditions for each skill. In this case, we can express the change in the relative price of skill as

$$\text{(12)} \quad \Delta P_c^S \approx \frac{PC_c}{L_c} - \Delta\ln s_c + \mu_c^{PC}$$

Now using 12 to replace the price of skill in 4 and 5, we obtain

$$\text{(13)} \quad \Delta MFdiff_{ec} \approx \beta_e^1\frac{PC_c}{L_c} - \beta_e^1\Delta\ln s_c + \beta_e^1\mu_c^{PC} + \Delta\varepsilon_{ec}$$

$$(14)\quad \Delta E_{ji}diff_{gc} \approx \beta^2_{jig}\frac{PC_c}{L_c} - \beta^2_{jig}\Delta s_c + \beta^2_{jig}\mu_c^{PC} + \Delta\varepsilon_{e_{ji}c}$$

Equations (13) and (14) now make more explicit the relationship between the gender wage gap, returns to education and technological change. In particular, these equations indicate that greater PC adoption should be associated with a greater reduction in the gender wage gap and a greater increase in the return to education. Moreover, it suggests that a faster increase in the relative supply of skills should be associated with increases in the gender wage gap and decreases in the returns to skill. The difficulty with these two equations, relative to equations (10) and (11), is that they are much more prone to endogenity. In particular, observed adoption of PCs will be correlated with local efficiency of PC use (μ_c^{PC}).[13] To address the endogeneity of PC adoption, we use 1980 measures of skill supply as the instruments, under the assumption that pre-PC-era skill supplies were not anticipating PC efficiency. The formulation given by equations (13) and (14) also highlight the potential use of PC adoption as an instrument for estimating equation (6). Although PC adoption is endogenous and correlated with μ_c^{PC}, this terms does not enter the error term in equation (6) and hence is potentially a valid candidate as an instrument.

In summary, our model of capital-skill complementarity in a two attribute model has highlighted different factors that should cause opposite movements in the gender gap and the returns to education. Furthermore, the model provides insight regarding what instruments are potentially admissible for exploring these relationships. In the empirical section we will examine all these implications to show that the ideas behind this simple model find considerable support in the data. Once this is shown, we will discuss how the estimated relationships based on cross-sectional observation can be used to evaluate the role of skill price changes in explaining the decrease in the aggregate gender wage gap observed over the 1980-2000 period.

[13]The change in the local supply of skill is also possibly correlated with the error terms in (13) and (14), something we will discuss further below.

2 Data and Empirical Methods

Our empirical investigation will focus on estimating the main relationships described in the previous section (these are equations (6), (10),(11), (13) and (14)) using data on aggregate outcomes drawn from U.S. metropolitan areas. We will begin this section by discussing the data and then we will further discuss implementation and identification issues.

2.1 Data and Measures

Our goal is to estimate three types of relationships across 230 U.S. metropolitan areas. First, the relationship between male-female and education wage gaps as described in (6). Second, the relationships between the pre-PC era supply of skill and each of the two wage gaps – the gender gap and the returns to education – as described in (10) and (11). And finally the relationship between the use of PCs and the two wage gaps as described in (12) and (13). To this end, we compute wages and skill supplies "pre-PC" using the 5% public-use version of the 1980 Census of Population (Ruggles et al., 2010), and "post-PC" using the 2000 Census of Population. Skill mix 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 further subsample 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 two and 200 dollars in 1999 dollars.

Male-female wage gaps are constructed separately for five education groups that can be consistently identified across censuses: high school dropouts, high school graduates, those with some college education (but less than four years), four-year college graduates, and advanced degrees.[14] As compositional changes are known to have substantially affected the

[14] 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."

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 includes a linear control for years of education and its interaction with the dummy for being born after 1950 for these groups.[15] 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.[16]

The main education wage gap we use on the right hand side is the simple average of male and female adjusted college-high school wage gaps (which come from the same adjustment procedure). We use the average to avoid any possibility of there being a "mechanical" relationship between the left- and right-hand side wage gaps.

Our empirical implementation of the quantities of "soft-cognitive skill " and "raw labor" consists of the following. First, raw labor input is assumed to vary only with gender and not with education, and we normalize $\gamma_f^l = 1$, so γ_m^l can be written as $1 + \Theta$, for some $\Theta > 0$, which will be estimated from average male-female wage gaps (described below). Letting ℓ_{ct}^M and ℓ_{ct}^F represent aggregate hours worked by men and women, respectively, in local labor market c in year t, we therefore define

$$(15) \quad L_{ct} = (1+\Theta)\ell_{ct}^M + \ell_{ct}^F.$$

[15] In neither census is there literally a "years of education" variable, but categories of years (1980) or degrees (2000). 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.

[16] 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 $MFdiff_{ect} = a_{emct} - a_{efct} + (\hat{\beta}_{emt} - \hat{\beta}_{eft})'\overline{X_{eft}}$.

Next, we impose that cognitive skill is linearly increasing in years of education above ten years (and is flat below that) by the same amount for both genders, which roughly describes the relationship between wages and education by gender. (See Figure A1 in online Appendix). That is, we define

$$(16) \quad S_{ct} = \sum_e \lambda \cdot max[(e - 10, 0)]\ell_{ect},$$

where ℓ_{ect} represents the aggregate hours worked of all persons with e years of schooling living in metropolitan area c and year t, and λ is the return to schooling.

To obtain estimates of Θ and λ we use the wage sample with more than 10 years of education in the 1980 Census to estimate an individual level regression of ln(hourly wage) on years of schooling and a male dummy. The coefficient on schooling is $\hat{\lambda} = 0.077$, and on the male dummy is $\hat{\Theta} = 0.423$. Substituting these into (15) and (16) generates our estimates of $\hat{L}_{ct}$ and $\hat{S}_{ct}$ and our skill mix measure, $\hat{s}_{ct} = \hat{S}_{ct}/\hat{L}_{ct}$. Note that this translates education and hours worked into human capital using fixed coefficient in all cities and years. (The choice of $\hat{\lambda}$, in particular, is immaterial.)

This skill mix measure may appear unusual, and it imposes the extreme assumption that gender wage gaps are entirely driven by gender differences in raw labor input per hour.[17] However, in both 1980 and 2000, it is highly correlated with a more conventional skill mix measure used in studies of the effect of computerization on skill demand: the natural log of the ratio of college "equivalent" to high school equivalent hours.[18] (See Figure A2 in online Appendix).

Our measure of computerization is personal computers per worker at the average employer

[17] In contrast, for example, just controlling for a gender-specific quartic in potential experience reduces the estimate of $\hat{\Theta}$ to 0.12.

[18] As in Card(2009), Figure 3 defines college equivalents as those with a four year degree plus 0.4 share of those with 1-3 years college. High school equivalents are 0.6 share of those with 1-3 years college, plus all of those with exactly 12 years, plus 0.7 share of those without a high school degree. (The fractional divisions derive from the workers in an education group supplying less than one efficiency unit per hour and/or dividing their labor supply between college and high school tasks.)

in the metropolitan area, adjusted for three-digit (SIC) industry crossed with size category dummies. The underlying data are firm level data collected by the marketing firm Harte-Hanks in 2000 and 2002. For simplicity, we will refer to this as "2000" data.

(Weighted) 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 five education groups. As has been documented elsewhere, the male-female wage gap declined over this period, by about 12 log points in our data. This decline was largest between less-educated men and women. Table 1 also shows there is "something to be explained" - there is variation in the level and 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 returns to education in the way the model suggests.

2.2 Addressing Potential Threats to Identification

There may be factors besides skill prices which drive the relationship between male-female and education wage gaps, or between the wage gaps and initial education – our ultimate source of variation – which would bias our inferences. There are at least four such potential factors. First, selection: Mulligan and Rubinstein's (2008) (MR) claim that rising returns to skill differentially induced entry of high skill women into the labor market, shrinking the gender wage gap through a change in the selection of working women from negative to positive. Second, labor force attachment: the importance of Mincer and Polacheck's (1974) explanation for the gender wage gap – that women interrupt their careers to have children – may have diminished as women's labor force attachment has increased.[19] Third, discrimination: declines in gender discrimination may have occurred differentially across markets during this period. Fourth, other compositional differences across markets, such as industry mix, that can affect changes in the gender wage gap.

[19] The diffusion of new birth control technology may have driven this (Goldin and Katz, 2002; Bailey, 2006). Bailey, Hershblein, and Miller (2012) provide evidence that early legal access to the birth control pill induced women to increase the total hours worked by a given age, among other investments in skills.

The selection phenomenon that MR describe has great potential to bias our estimates. In our model, education and male female wage gaps are negatively correlated because of common unobserved skill prices, but in the MR story they are related for a different reason: high returns to skill differentially induce high skill women to enter the workforce. Technological change may have reduced the male-female wage gap between 1980 and 2000, but in MR's view it is entirely through changes in selection (rather than through changes in the "quality constant" male-female wage gap).[20] However, using a related but different approach (discussed further below), Machado (2011) finds changes in selection are responsible for none of the decline in the male-female wage gap over the period. Nevertheless, it remains important for us to address this potential confounder.

We do three things to address MR's selection story. First, and most simply, we control for female employment rates. As these could be endogenous outcomes of wages, however, we use and interpret these controls cautiously. Second, in a robustness checks section we will include estimates which control for selection in a manner similar to the way MR did. We will use an inverse mills ratio transformation of the predicted probability of female employment, using the presence of kids under age six in the household (whose effect is allowed to vary by marital status) as an instrument for female employment. Further details on this estimation strategy are below. In keeping with MR, this selection correction is allowed to vary by year, and in our case, regionally. Third, like both MR and Machado, we will examine groups of women who likely have high labor force attachment, therefore whose employment is likely less sensitive to the wage structure (also in the robustness checks).

To minimize the influence of unobserved differences in female work experience across markets and over time, all of our wage gaps are adjusted for for gender (x education x year)-specific potential experience profiles. In addition, since changes in labor force attachment largely occur across (birth) cohorts, in robustness checks we will show estimates which examine

[20]MR do not take a stand on what is generating the changes in the return to skill. Note that even in the MR story, selection may or may not bias our estimates: our male-female wage gaps condition on education (in addition to other observables, described below), so the MR-type bias will arise only if *residual* wage gaps are also larger in more high skilled cities.

within cohort changes in the gender wage gaps (restricting the sample to men and women from the same birth cohort in both years).

We do not have strong reason to believe differential changes in gender discrimination biases our estimates, but to help control for this, we will include estimates that control for state fixed effects. Among other things, these capture the effect of any state-level legislation improving the rights of women.

Other compositional differences could be correlated with skill mix and changes in the relative wages of females. One plausible source of potential bias is differences in industry mix across metro areas. Olivetti and Petrongolo (2011) find that differences in industry mix can account for a substantial portion of cross-country differences in the gender gap. In addition, during this time period the decline in the wages of less-skilled men in manufacturing could have simultaneously lowered male-female wage gaps and raised college-high school wage gaps in manufacturing-intensive locales (which is correlated with being a less-skilled locale).[21] While some of this might be due to technological change, some of it might be due to other forces (like a decline in union power). Therefore we will control for measures of industry mix, and manufacturing share in particular (described below). To address the possibility that other types of compositional differences bias our estimates, we will also evaluate the sensitivity of our estimates to controls for demographic mix (e.g., black share, immigrant share) as well as the natural log of the labor force and unemployment rate, all measured in our initial year. The latter can help account for, for example, gender differences in the impact of the business cycle (e.g., Hoynes, Miller, and Schaller, 2012).

[21] O'Neill and Polachek (1993) find that the decline in blue collar wages accounts for a quarter of the decline in the male-female wage gap in the 1980s.

3 Results

3.1 Ordinary Least Squares

Columns (1)-(7) of Table 2 shows OLS estimates of the relationship in equation (6), between changes in the male-female and college-high school wage gaps between 1980 and 2000, with various sets of controls. The controls have been demeaned so that the intercept, which is shown, can be interpreted as the counterfactual change in the male-female wage gap in a location with the average value of controls but no increase in the returns to college. (See Section 5, below.) The estimates also pool together gender wage gaps for our five different education categories (and, again, standard errors are calculated to be robust to error correlation across education groups in a metro area).

Controlling only for education group effects (which by definition make no difference to the point estimates, since the education wage gap does not vary across education groups) produces a coefficient of -0.231, or that a one percentage point increase in the return to college is associated with a 0.231 percentage point decline in the male-female wage gap. Despite having (what is likely a very) noisy right-hand side variable, this relationship is highly significant.

Other columns of Table 2 add controls. In light of Olivetti and Petrongolo (2011), we believe that it may be important to control for industry mix. So in columns (2)-(4) we explore three different versions of industry mix controls. To begin with, we control for durable and non-durable manufacturing employment shares, measured in 1980, whose impact is allowed to vary by the two, what we will call "broad," education categories that Olivetti and Petrongolo (2011) used: (1) workers with some college or below or (2) four years of college or more.[22] As expected, this lowers the coefficient, as the decline in male wages in manufacturing-intensive locales lowers both male-female and raises college-high school wage gaps. These controls do not, however, account for all of the OLS relationship.

[22]Defining broad education groups this way is also consistent with evidence suggesting that workers of different education levels within these broad groups are near perfect substitutes (e.g., Goldin and Katz, 2008).

Differences in the size of manufacturing may be the most plausible source of industry-mix driven bias, but they may not be the only source.[23] However, with only 230 metro areas, adding detail to the industry mix controls can quickly make estimates imprecise and will also tend to make measurement error attenuation worse. So we have tried to find parsimonious ways of controlling for detailed industry mix. In column (3) we use an alternative wage adjustment (for the dependent variable) which controls for a full set of census industry dummies.[24] These estimates are larger than the ones in column (2). This may mean that detailed industry controls make little additional difference, though the estimates in column (3) are also conceptually different – they are within industry gender wage gaps, and so do not capture any broader effects of industry mix on wage gaps of men and women not in a particular industry. To account for this, in column (4) we control for the manufacturing shares as before, and add an index which measures the average "womanpower" requirements of the local detailed industry mix (in 1980), as in $\frac{\sum_j f_{jb}\ell_{jc}}{\sum_j \ell_{jc}}$, where f_{jb} represents 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. This is calculated separately for the same two broad education groups as before.[25] These estimates are similar to column (2), but with the smallest standard errors of any of the approaches. This reinforces the value of using a parsimonious set of controls. Throughout the rest of the paper we will use these as our controls for industry mix.

Regional differences in the extent of gender discrimination might affect our estimates. These are very difficult to quantify. To at least try to capture the effects of state policies which might affect the male-female wage gap, we control in column (5) for state dummies. The

[23]We found that adding other two-digit sector employment shares as controls has little additional impact on the point estimate, though it does make the standard errors larger.

[24]We use the approximately 200 industry categories that are harmonized to 1990 industry categories (Ruggles et al., 2010). These controls are in addition to the other controls included in the wage adjustment, described in the previous section, which is again separately estimated by gender, education group, and year.

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

coefficient is larger in magnitude with this control, suggesting such policies do not work in the same direction as our results.[26]

Column (6) adds a few other controls which might have a compositional impact. These include the share foreign-born, black, and Hispanic, and the unemployment rate and the natural log of the the city's labor force. The latter two attempt to capture any differences in sensitivity of male-female wage gaps to the business cycle or agglomeration effects. The others might shift skill and gender ratios where they settle (recall that wage gaps are already adjusted for nativity, race, and ethnicity at the individual level). Column (7) controls for female employment rates by broad education. This is our first pass at controlling for selection. These controls have only a little impact. Recognizing that this control is endogenous, we added it last, and in the robustness checks section, we examine other methods for correcting for selection.

Column (8) replaces the independent variable, the college-high school wage gap, with (similarly regression-adjusted and averaged over men and women) estimated linear return to schooling (above 10 years), multiplied by four. The estimates using this measure are quite similar, though less precise. They may be less well measured because of the need to interpolate education categories into a linear "years of education," which is constructed differently in 1980 and 2000 because of the change in how education is coded. We believe these coding changes are likely less of a problem for measuring the wage gaps between college and high school workers. So we will continue using college-high school wage gaps as our main measure of education wage gaps.

[26] 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.

3.2 Relationship to Skill Mix

Now we turn to reduced form estimates of the relationship between wage gaps and our proxy for the initial relative abundance of soft-cognitive skills, $\hat{s}_{c,1980}$, which we will call "human capital/raw labor." As outlined in the theory section, this is expected to have opposite-signed relationships with changes in male-female and changes in college-high school wage gaps. In particular, as (10) and (11) described, initial human capital is expected to have a negative relationship with the change in male-female wage gap and a positive relationship with the change in college-high school wage gap.

Table 3 shows the relationship of the male-female (in Panel A) and college-high school (in Panel B) with skill in 1980. As before, column (1) controls only for education group dummies. The coefficient on $\hat{s}$ is negative in Panel A and positive in Panel B, as the theory predicts. For the most part, the controls have little impact on these relationships, though the industry controls, added in column (2) enlarge the magnitude of both relationships a bit. The high stability of the estimates in panel B is particularly reassuring for the validity of the approach we are taking, because Panel B estimates are also the "first stage" relationship for the main IV estimates of the relationship between changes in male-female and college-high school wage gaps (below). Figure 2 shows residual plots of the bivariate relationship between the changes in wage gaps, corresponding to the first four columns of Table 3. Reassuringly, the relationship does not appear to be driven by any particularly influential points.

3.3 PC Adoption

Tables 4a shows the relationship between PCs per worker in 2000 and the 1980-2000 change in male-female wage gap, while Table 4b shows the relationship with the 1980-2000 change in the college-high school wage gap. PCs per worker in 2000 is a proxy for the intensity of computer adoption over 1980-2000, in light of the fact that PCs per worker was zero in 1980. As per equation (13) and (14), all regressions control for the change in skill mix over the period (although this turns out to make little difference).

Panel A of Table 4a shows least squares estimates. The coefficient on PCs in column (1) with limited controls is -0.204, which says a 0.1 increase in PCs per worker (a little more than a standard deviation – Table 1) is associated with a 2.4 percentage point decline in the growth of the male-female wage gap. As expected, an increase in skill supply, $\Delta\hat{s}$ is associated with an increased male-female wage gap.[27] The industry controls have little effect on the relationship with PCs, while controls added in other columns diminish the relationship.

As discussed in the theory section, OLS estimates are expected to be biased towards zero by unobserved factors which make PCs more productive. Panel B shows instrumental variables estimates, where the personal computer variable is treated endogenous, and the instrument is 1980 human capital/raw labor. First stage F-stats are shown below Panel B. Without controls other than education effects, the first stages F-stat is 136, and with all of the controls it is 63, both quite strong. Figure 3 also shows the bivariate relationship between PCs per worker in 2000 and skill mix in 1980 is strong and not driven by outliers, consistent with other work showing a relationship between local skill mix and PC adoption (Caselli and Coleman, 2001; Doms and Lewis, 2006). As expected, the point estimates in Panel B are larger. In addition, unlike OLS estimates, they also do not generally diminish with the addition of controls. The point estimate here suggests a 0.1 increase in PCs per worker lowers the male-female wage gap roughly four percentage points.

The change in skill mix is treated as exogenous in Panel B, though it may not be. To address this, we tried a couple of things. First, we used the size of immigrant "enclaves" in 1970 to predict changes in skill mix 1980-2000, exploiting the fact that there was a boom in immigration over this period, and that immigrants tend to cluster near immigrants of the same origin. Though this variable does a reasonable job of predicting changes in skill mix, it does not have enough power to do so within state, so the approach does not work once state effects are controlled for. Nevertheless, using this approach, the estimates without state effects are quite similar to the estimates in columns (1) and (2) of panel B.[28] In addition, we

[27] In equation (13), recall, the parameter β_e^1 is expected to be negative.

[28] In particular, the coefficient estimate (standard error) on PCs per worker with just education group effects is -0.242(0.064) and with industry mix controls is -0.339(0.080) when we add the ethnic enclave instrument and treat changes in skill mix as endogenous. The corresponding coefficient on skill mix changes

tried dropping the change in skill mix as a control. As can be seen in Appendix Table A1a, this has little effect (on either the OLS or IV estimates).

Table 4b performs a parallel set of estimates where the dependent variable is the change in the college-high school wage gap. The pattern of estimates is quite similar to Table 4a, except, as expected, with coefficients of the opposite sign. The alternative instrumental variables strategies produce similar estimates in this case as well.[29] In summary, U.S. labor markets with greater PC adoption tend to experience both faster increases in the college-school wage gap and faster declines in the male-female wage gap.

3.4 IV estimates of the co-movement between the gender gap and the returns to college

Table 5 puts together the male-female and education wage gap results into instrumental variables estimates (which are the ratio of coefficients in panels A and B of Table 3). All of the estimates show a negative significant relationship between the wage gaps, with a magnitude roughly around 0.6-0.7. This is larger in magnitude than the OLS estimates in Table 2, consistent with OLS estimates being attenuated. It is, however, approximately the same magnitude of comovement found in the aggregate. In particular, a regression using aggregate annual data for 1980-2000, stacking adjusted male-female gaps (for our same five education groups) on college-high school gaps produces a coefficient (standard error) of -0.710 (0.0452).[30]

are 0.796(0.227) and 0.862(0.267).

[29]With the ethnic enclave instrument added, the coefficient (standard error) on PCs in column (1) would be 0.425(0.129) and in column (2) would be 0.458(0.179). The point estimates on the change in skill mix are -2.049(0.480) and -2.238(0.600) for columns (1) and (2), respectively. Estimates dropping the change in skill mix control can be found in Appendix Table A1b.

[30]Standard error clustered on year. Wage series constructed using merged outgoing rotation groups of the Current Population Survey, using only data on those aged 16-65 with positive (potential) work experience (age - years of schooling - 6 $>$ 0), positive wage and salary earnings and hours worked in the past year, and currently in the labor force. Hourly wages were "Windsorized" to be between two and 200 dollars in 1999 dollars. Some of the wage series used in the regressions are shown in Figure 1.

In light of the significant relationship between wage gaps and PC adoption, another approach is using PC adoption as an instrument.[31] PC adoption is, after all, our proxy for the "treatment": the adoption of computers is what we hypothesize is driving the changes in the wage structure. In addition, recall that the error term of the ("first stage") relationship between education wage gaps and PCs, (14), is, according to the theory, uncorrelated with the error in the wage gap relationship we are trying to identify, (6). In practice, the IV estimates we get using our PC adoption variable as the instrument are a bit more sensitive to controls (see Appendix Table A2), though they are in the same ballpark.[32]

4 Robustness Checks

In this section, we examine three important robustness checks: (1) To what extent are our estimates driven by changes in the selection of women into areas' workforces? (2) To what extent are the estimates driven by the cohort composition of women? And, (3) does the timing of wage changes match the timing of the arrival of PCs, or were there similar changes in wage structure occurring before the arrival of PCs? The first is an important alternative explanation for the aggregate trend in Figure 1 raised by MR; we need to establish whether similar changes in selection correlated with changes in returns to education occurred differentially across metropolitan areas. The second speaks to another alternative source of changes in male-female wage gap over this period: the greater labor force attachment of more recent cohorts of women. Finally, it is important to establish whether similar wage structure changes predated computerization.

4.1 Is It Selection?

In a prominent recent paper, MR argue that rising returns to skill have induced the selection of women into work to become more positive. This suggests an alternative mechanism for

[31] The first stage corresponding to this IV specification is shown in panel A of Appendix Table A1b.

[32] Coefficient estimates (standard errors) range from -0.940(0.491) to -0.425(0.310).

our results so far: rather than being driven by common unobserved skill prices, the negative relationship between changes in college-high school and male-female wage gaps might be due to differential changes in selection. To investigate this possibility, in Table 6 we apply a variety of selection correction methods to our data. Some of these methods are data intensive, and so in this section we restrict our sample to a set of 181 larger metropolitan areas where these methods are feasible.[33]

Column (1) of Table 6 shows the estimated relationship between male-female and college-high school wage gaps in this subsample, with OLS estimates in Panel A, and instrumental variables estimates in Panel B. These estimates have the same controls as column (6) of Table 2 (for OLS) and column (4) of Table 5 (for IV). Compared to those, column (1) shows the estimates in this subsample are similar, if slightly smaller in magnitude. Columns (2) - (3) compute male-female wage gaps only using female demographic groups with a high probability of working. MR argued that this allowed for "identification at infinity": intuitively, women with a high probability of working are plausibly less sensitive to the wage structure in their employment decisions, and so their wages are likely less biased by selection. One way in which we identified women with a "high probability of working" is as follows. We estimated, separately for each education group, probits for being in the wage sample, that is

$$(17) \quad Pr(wgobs_{ic}) = \Phi\left(a_c + \beta' X_{ic} + \Gamma' Z_{ic} + \epsilon_{ic}\right),$$

where $Pr(wgobs_{ic})$ represents the probability that woman i in metro area c meets our criteria for being in the wage sample (see Data section). The probit includes metro area fixed effects, a_c; a vector of adjustment controls, X_{ic}, which are identical to what is used in to adjust wages in earlier estimates but also includes dummies for marital status and their interaction with black, Hispanic, and foreign-born; and a set of instruments Z_{ic}, used by MR, that are two-

[33]Specifically, we limit the sample to metro areas with at least 100 wage observations in all five education groups in both 1980 and 2000, for which the probits for female employment converged within 10 iterations for all five education groups, and for which male and female wage observations were available for all five education groups for all of the subsamples examined in Table 6.

way interactions between marital status and presence of children under age six, which we further interact again with black, Hispanic and foreign-born.[34] (Although the validity of these instruments is questionable, something MR acknowledge, we nevertheless would like to probe the sensitivity of our results to using them.) We constructed the predicted values for the average metro area, that is, putting in $\overline{a}$ in place of the vector of estimated fixed effects. We define women with a high probability of working as those with at least a 0.6 probability of working. To avoid compositional changes, we estimate this probit using the 1980 data alone, and apply the same estimates to define such women in 2000.[35]

Estimates using this subsample of women are shown in column (2). The estimates are smaller than in column (1) but still negative. Column (3) takes a simpler approach with the same motivation, looking only at what we will call "nonminority" (native-born non-Hispanic white) never-married women without kids under age 6, who we compare to nonminority men. The estimates in this subsample are larger in magnitude.

Another MR-derived approach we can take is to use the full sample of women but control for selection. In performing the wage adjustments on women, we control for an inverse mills ratio transformation of the estimate of (17) (now allowed to vary by year) which accounts for selection under the assumption of normal errors.[36] The estimates, shown in column (5) are smaller in magnitude than in column (1) in IV and larger in OLS. Not shown is the fact that the mean of our selection adjusted male-female wage gap replicates the result of MR: there is no longer any *average* decline in male-female wage gap once this adjustment is made. Nevertheless, this adjustment does not eliminate the correlation between changes in wage gaps across metro areas.

[34]MR limit the sample to white non-Hispanics. We have tried this as well. It has little effect on the estimates, but, predictably, leads the standard errors to be a bit larger.

[35]By 2000, the probability of women working had shifted up, so the women who met this threshold in 2000 also would have at least a 0.6 probability of working.

[36]In the wage adjustment step, we add to the list of controls described in the Data section marital status controls interacted with dummies for black, Hispanic, and foreign born; and, for females, the interaction of the inverse mills ratio with dummies for black, Hispanic, and foreign born. The adjusted wages are evaluated at the national mean of female characteristics and with the inverse mills ratio set to zero.

One of the key points MR raise is that the selection function itself may depend on the wage structure. So rather than just estimate a single probit for each year x education group, in column (6) we allow the probit estimates to vary by metro area. These estimates making these adjustments, in column (6), are not smaller in magnitude than in column (1). Estimating the adjustment separately for each MSA clearly pushes the data beyond its limits, leading the estimates to be very imprecise and to include zero in the confidence interval.[37] So it perhaps fair to say that these estimates do not completely rule out that selection is driving our results. However, the point estimates here, combined with earlier results which control for female employment rates, suggest changes in selection explain very little the observed comovement of wage gaps. In addition to these results, female employment rates are not differentially rising more quickly in markets which have higher initial levels of human capital/raw labor. (See Appendix Table A3).

While we should not necessarily expect to get the same results as MR, who use a totally different source of variation, we should note that the literature is not entirely settled on the view that changes in selection have driven down the male-female wage gap in the aggregate. In particular, Machado (2011) argues that MR's methods are overly restrictive, imposing the same selection function for all women. Instead of a parametric selection correction she essentially argues that one should examine the wages of working women *with* young kids. She argues these women are likely to have also been working in the absence of having kids (an assumption she provides some evidence for), and being highly attached are therefore more comparable to men.[38] Comparing young women with young kids to young men, she finds that selection can account for none of the decline in the male-female wage gap between 1980 and 2000.[39]

[37]In many metro area-education group-year cells in the probit, the coefficients on the Z's are also not jointly significant, making the estimates only identified off of functional form.

[38]Her argument essentially derives from the monotonicity condition for valid IV estimation under heterogeneous treatment effects. All the women who work and have kids would have been working if they did not have kids, because having kids only makes it less likely that you work. A necessary condition for this is that women with kids are on average less likely to work, which she shows holds in all the subgroup x year cells she examines.

[39]This is also consistent with Blau and Kahn (2006). Using methods similar to Neal (2004), they show

We examine the "Machado subsample" – women with young kids – in column (4) of Table 6. The IV estimates are large, negative, and significant in this subsample. So again, we are not finding evidence that selection is driving our results.

4.2 Is it Changes in Cohort Composition?

One reason our estimates could be overstated areas which are initially more educated may tend to have younger workforces, and the greater labor force attachment of younger cohorts, driven by the availability of birth control technology, may have contributed to a decline in the male-female wage gap (Bailey, Hershblein, and Miller, 2012, hereafter, BHM). However, in online Appendix B, we show that college-high school wage gaps negative covary with even within birth cohort changes in the male-female wage gap.[40]

4.3 The Timing of the Changes

As an additional test of the model, in Table 7 we examine more closely the timing of the changes. Our key empirical fact is that changes in the male-female and college-high school wage gap moved in opposite directions in the 1980-2000 period. We argued that this was due to the arrival of PCs during this period, which resulted in a shift in the production and wage structure. Because PC adoption is likely endogenous, we used 1980 skill mix to identify the relationship. If we find similar relationships prior to the introduction of PCs, therefore, it would cast serious doubt on the interpretation that the relationship was being driven by the introduction of PCs.

To see if this is the case, in Table 7 we examine the same relationships before and after the PC is introduced. It turns out only to be possible to consistently construct our variables in

that if you use work histories and other information to infer where non-working men and women would be in the wage distribution, you can account for very little of the increase in the female relative to male median wages between 1979 and 1998.

[40]This within cohort relationship is a bit smaller in magnitude than our earlier results, consistent with some role for the phenomenon BHM describe.

137 metropolitan areas in the 1970, 1980 and 1990 (and not 2000) Censuses.[41]

Panel A shows the OLS relationship between changes in male-female and college-high school wage gaps, like in Table 2, but with the smaller sample. Column (1) shows the relationship in the "pre-PC" (1970-1980) period. Unlike in Table 2, there is no significant relationship. Column (2) makes clear that this not because of the change of sample or methods, because 1980-1990, using the same methods, there is a negative significant relationship between the changes in wage gaps, which is, if anything, larger in magnitude that comparable estimates (in column (6)) in Table 2. There is also a significant relationship in this sample 1980-2000 using our original wage construction methods in this sample (column (3)).

Panel B looks at the relationship between the change in the male-female wage gaps and the instrument, 1980 human capital/raw labor. Column (1) of Panel B shows that although the reduced form relationship is negative 1970-1980, it is not significant.[42] The point estimate is also much larger after 1980 than before. The size of the standard errors in column (1) are unfortunate, because it means we cannot totally rule out similar pre-PC trends in the male-female wage gap. But the relationship appears to at least be much weaker before the arrival of PCs.[43]

[41]The 1970 census is both much smaller and has much less detailed measures of geography and hours worked than later censuses. (These issues are detailed in the notes to Table 7.) It also turns out that only with the 1970, 1980, and 1990 censuses can we construct wage measures entirely consistently, as the 2000 Census does not include the "hours worked last week" variable that is available in those years. The 1970 data come from the two one percent public-use "county-group" files, and the 1990 data are from the five percent public use data (both Ruggles et al., 2010).

[42]The "first stage" relationship with the change in the college-high school wage gap 1970-80 is also not significant, which is why we show the reduced form rather than the IV estimate.

[43]It is also possible that a weak relationship exists in the 1970s because at least some similar technological change occurred before the arrival of PCs. For example, Autor, Levy, and Murnane find evidence of shift in the skill-biased shift in the task content of the economy in the 1970s that is similar in nature and smaller in magnitude than later decades.

5 Implications for Aggregate Outcomes

We started this paper with the observation that the wage differential between men and women with similar levels of education decreased substantially between 1980 and 2000, while at the same time the return to education increased substantially. As suggested by, among others, Welch (2000), this decrease in the gender wage gap could reflect a change in a the relative price of skill which is more abundant among women and more educated workers. We have now shown that this idea finds considerable support also in cross-city data: the male female wage differentials and the return to education at the city level appear to react in opposite directions to factors that likely influence the relative price of soft-cognitive skills versus hard-raw motor skills. In this section we want to discuss how our cross-city estimates can be used to infer about the potential role of changes in skill prices in explaining the decrease in the aggregate male-female wage gap between 1980 and 2000.

There are two ways of using our cross-city estimate to evaluate the role of skill prices changes in explaining the gender wage gap. First, if we are ready to assume that the aggregate movement in the return to college reflects mainly a change in the relative price of skill, then we can use our estimates of $\frac{\beta^1}{\beta_2}$ obtained from the IV estimation of equation (6) to calculate the contribution of increase in skill price on the the gender gap. In particular, over this period we observed the return to college increase by 19.2 percentage points. If we multiply this by our estimates of $\frac{\beta^1}{\beta_2}$ reported in Table 5, we get predicted effects on the male-female wage differential ranging from -10.2 to -15.9 percentage points. Since the decrease in the male-female wage differential over this period was approximately 12.4 percentage points, this exercise implies that essentially all of the decrease in the gender wage gap can be explained by the change in the relative price of skills. The OLS estimates of the relationship (Table 2) can account for about one-quarter.[44]

If we are not willing to assume that the change in the aggregate return to education over this period was driven only by a change in a relative prices, there is a second way to proceed.

[44] Our within cohort estimates (available online) can account for 60-80 percent, roughly complementing the 10-30 percent that BHM found was driven by early legal access to the birth control pill.

Starting from equation (6), consider taking a weighted sum of each term where the weights are the relative population weights of the cities. The weighted sum of the error terms (including any estimated intercept for this regression) then gives us an estimate of the change in the male-female wage differential which cannot be attributed to the change in the skill price. In fact, this can be seen by directly be examining our estimate of the intercept of this regression.[45] When we estimate this relationship by OLS (Table 2) we find that the intercept is significantly negative. In contrast, when we estimate this relationship by instrumental variables, we find that the intercept is insignificantly different than zero, indicating that on average across cities the "predicted" local increase in the returns to college – combined with the estimate of $\frac{\beta^1}{\beta_2}$ – is sufficient to explain the changes in the gender wage gap over the period.[46] Hence, we believe that that these two pieces of evidence point in the same direction: Most of the decrease in the gender wage gap over the 1980-2000 period can be attributed to a change in the relative price of a skill – which we have referred to as a soft-cognitive skill – that is more abundant among women and more educated workers.

6 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 were driven by a change in the relative price of an an unobserved skill which both women and educated workers have in abundance – we called it "soft-cognitive" skills – induced by skill biased technological change. This idea has been suggested before. But by exploring cross city variation in wages and skill mix between 1980 and 2000, we are able to move beyond the aggregate relationships and, for the first time, directly examine the relationship between the return to education and male-female wage gaps.

Consistent with the idea that females are relatively abundant in soft skills, we find that after the arrival of PCs, markets that experienced faster increases in the college-high school

[45]Recall that all of the controls are demeaned, and all regressions are weighted by 1980 population.

[46]We also find this when using PC use as the instrument (Appendix Table A2).

wage gap saw bigger drops in the male-female wage gap. This relationship remains strong when controlling for industry mix, or when examining differences in education wage gaps induced by our proxy for the supply of human capital: consistent with a standard model of skill-biased technological change, the decline in male-female and increase in education wage gaps was largest in initially human capital intensive markets.

As robustness checks, we show that 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. In addition, we show that there was no significant trend in the relationship between education and male-female wage gaps in the 1970s, before the introduction of PCs.

Overall, our estimates are consistent with a substantial role for changing skill prices in accounting for the decline in the male-female wage gap between 1980-2000. Even applying our OLS estimates, which we have reason to believe are substantially attenuated, suggests that the rise in the return to education between 1980 and 2000 accounted for one-fourth of the decline in the male-female wage gap over the period. Our IV estimates can account for most of the increase. This does not mean that other forces cannot influence gender equality in earnings. For example, our within cohort estimates are consistent with a non-trivial role for increased labor force attachment of newer cohorts of women.[47] However, it does suggest the historically dramatic decline in the male-female wage gap in the 1980s may have been largely driven by technological forces unique to that period. The relative stagnation of the male-female wage gap in more recent years may reflect that.

[47] 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.

References

Autor, David H., Frank Levy, and Richard J. Murnane. “The Skill Content of Recent Technological Change: An Empirical Exploration,” *Quarterly Journal of Economics*, 118(4): November 2003, pp. 1279-1334.

Bacolod, Marigee, and Bernardo S. Blum. “Two Sides of the Same Coin: U.S. ’Residual Inequality’ and the Gender Gap.” *Journal of Human Resources* 45(1): Winter 2010, pp. 197-242.

Bailey, Martha J. “More Power to the Pill: The Impact of Contraceptive Freedom on Women’s Lifecycle Labor Supply.” *Quarterly Journal of Economics* 121(1): February 2006, pp. 289-320.

Bailey, Martha J., Brad Hershblein. and Amalia R. Miller. “The Opt-In Revolution? Contraception and the Gender Gap in Wages.” *American Economic Review: Applied Economics* : May 2012.

Beaudry, Paul, Mark Doms, and Ethan Lewis. “Should the PC be Considered a Technological Revolution? Evidence from US Metropolitan Areas.” *Journal of Political Economy* 118(5): October 2010, pp. 988-1036.

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

—. “Changes in U.S. Wages, 1976-2000: Ongoing Skill Bias or Major Technological Change?” *Journal of Labor Economics* 23(3): July 2005, pp. 609-648.

Black, Sandra and Alexandra Spitz-Oener. “Explaining Women’s Success: Technological Change and the Skill Content of Women’s Work.” *The Review of Economics and Statistics* 92(1): February 2010, pp. 187-194.

Blau, Francine D. and Lawrence M. Kahn. “Swimming Upstream: Trends in teh Gender Wage Differential in the 1980s.” *Journal of Labor Economics* 15(1): January, 1997, pp. 1-42.

—-. “The US Gender Pay Gap in the 1990s: Slowing Convergence.” *Industrial and Labor Relations Review* 60(1): October 2006, pp. 45-66.

Card, David. “Immigration and Inequality.” *The American Economic Review* 99(2): May 2009, pp. 1-21.

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

Caselli, Francesco. 1999. “Technological Revolutions.” *American Economic Review* 89(1): May 1999, pp. 78-102.

Caselli, Francesco and John Wilbur Coleman II. “Cross-Country Technology Diffusions: The Case of Computers.” *American Economic Review Papers and Proceedings* 91(2): May 2001, pp. 328-335.

Doms, Mark and Ethan Lewis. “Labor Supply and Personal Computer Adoption.” Federal Reserve Bank of San Francisco Working Paper #2006-15, June 2006.

Fortin, Nicole M. and Thomas Lemieux. “Are Women’s Wage Gains Men’s Losses? A Distributional Test.” *The American Economic Review Papers and Proceedings* 90(2): May 2000, pp. 456-460.

Goldin, Claudia; Katz, Lawrence F. “The Power of the Pill: Oral Contraceptives and Women’s Career and Marriage Decisions.” *Journal of Political Economy* 110 (4): August 2002, pp. 730-70.

Goldin, Claudia and Larry Katz. *The Race Between Education and Technology.* Cambridge and London: Harvard University Press, Belknap Press, 2008.

Hoynes, Hilary W., Douglas L. Miller, and Jessamyn Schaller. “Who Suffers During Recessions?” NBER Working Paper No. 17951, March 2012.

Lemieux, Thomas. “The Mincer Equation Thirty Years after Schooling, Experience, and

Earnings." in S. Grossbard-Shechtman, ed., *Jacob Mincer, A Pioneer of Modern Labor Economics*, Springer Verlag, 2006.

Machado, Ceclia. "Selection, Heterogeneity and the Gender Wage Gap." Mimeo, Getulio Vargas Foundation, December 2011.

Mincer, Jacob and Solomon Polachek. "Family Investments in Human Capital: Earnings of Women" *Journal of Political Economy* 82(2, Part 2) March - April 1974, pp. S76-S108.

Minnesota Population Center. National Historical Geographic Information System: Pre-release Version 0.1. Minneapolis, MN: University of Minnesota, 2004; available at http://www.nhgis.org.

Mulligan Casey, B. and Yona Rubinstein. "Selection, Investment, and Women's Relative Wages." *Quarterly Journal of Economics* 123(8): August 2008, pp. 1061-1110.

Neal, Derek. "The Measured Black-White Wage Gap Among Women is Too Small." *Journal of Political Economy* 112(S1): February 2004, pp. S1-S28.

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

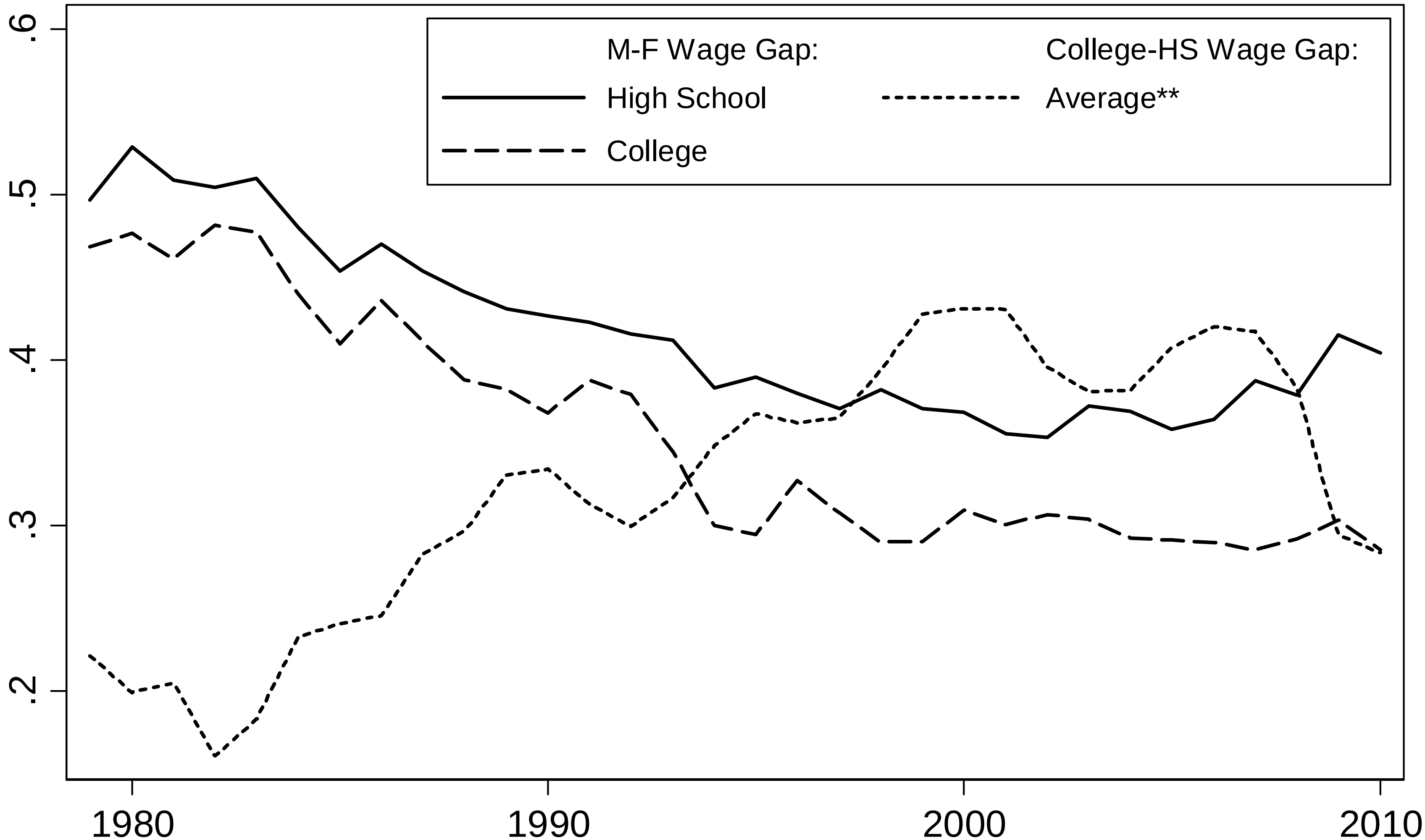
O'Neill, June and Solomon Polachek. "Why the Gender Gap in Wages Narrowed in the 1980s." *Journal of Labor Economics* 11(11): January 1993, pp. 205-228.

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

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

Welch, Finis. "Growth in Women's Relative Wages and in Inequality among Men: One Phenomenon or Two?" *The American Economic Review: Papers & Proceedings* 90(2): May 2000, pp. 444-449.

Figure 1. Male-Female, College-HS Wage Gap*, 1979-2010



*Adjusted for gender x year specific quartic in potential experience (age-years ed-6), evaluated at the female average over 1979-2010.
**Simple average of male and female adjusted college-high school wage gaps.

Figure 2. Residual Plots: Change in Wage Gaps, 1980-2000
vs. 1980 Human Capital/Raw Labor

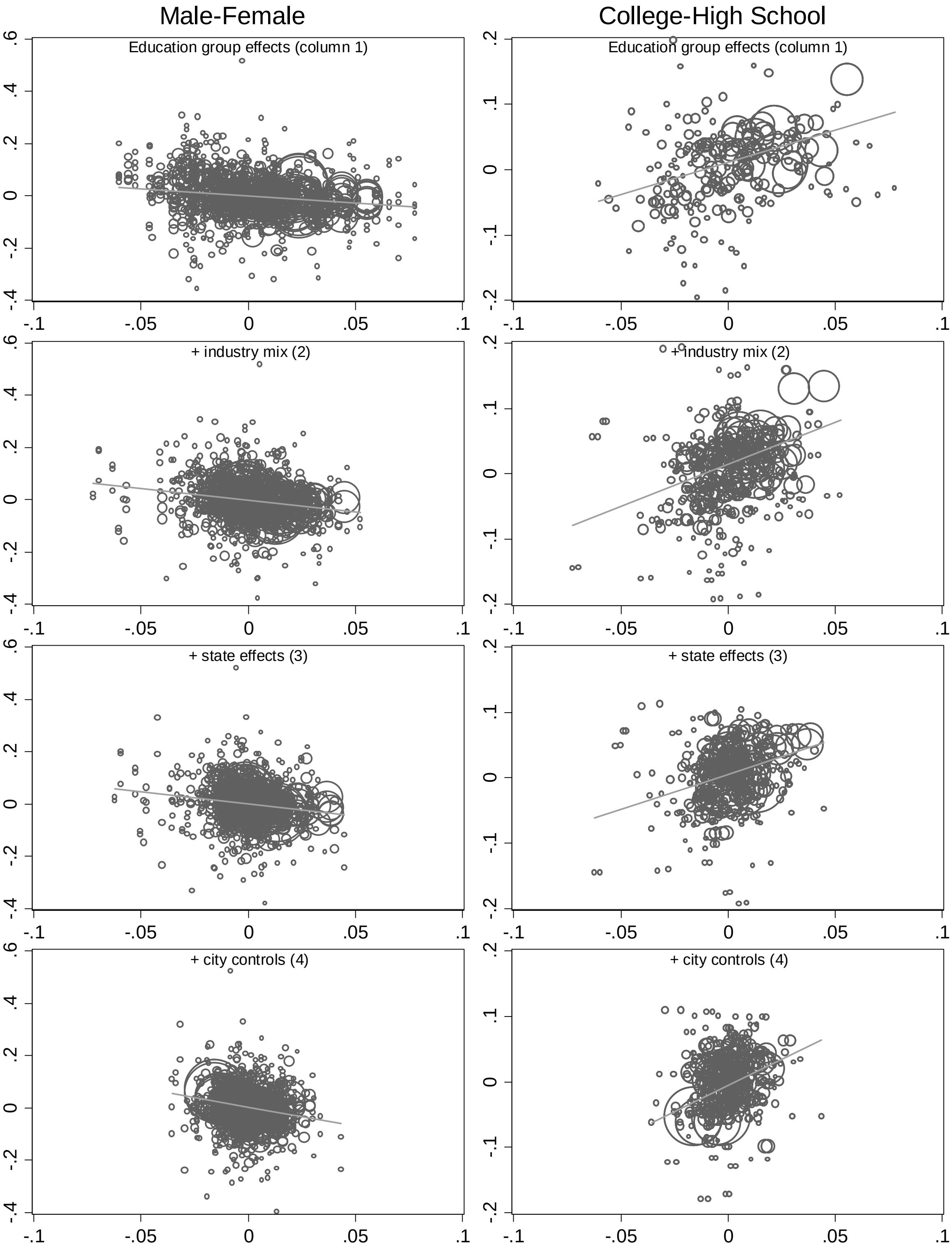
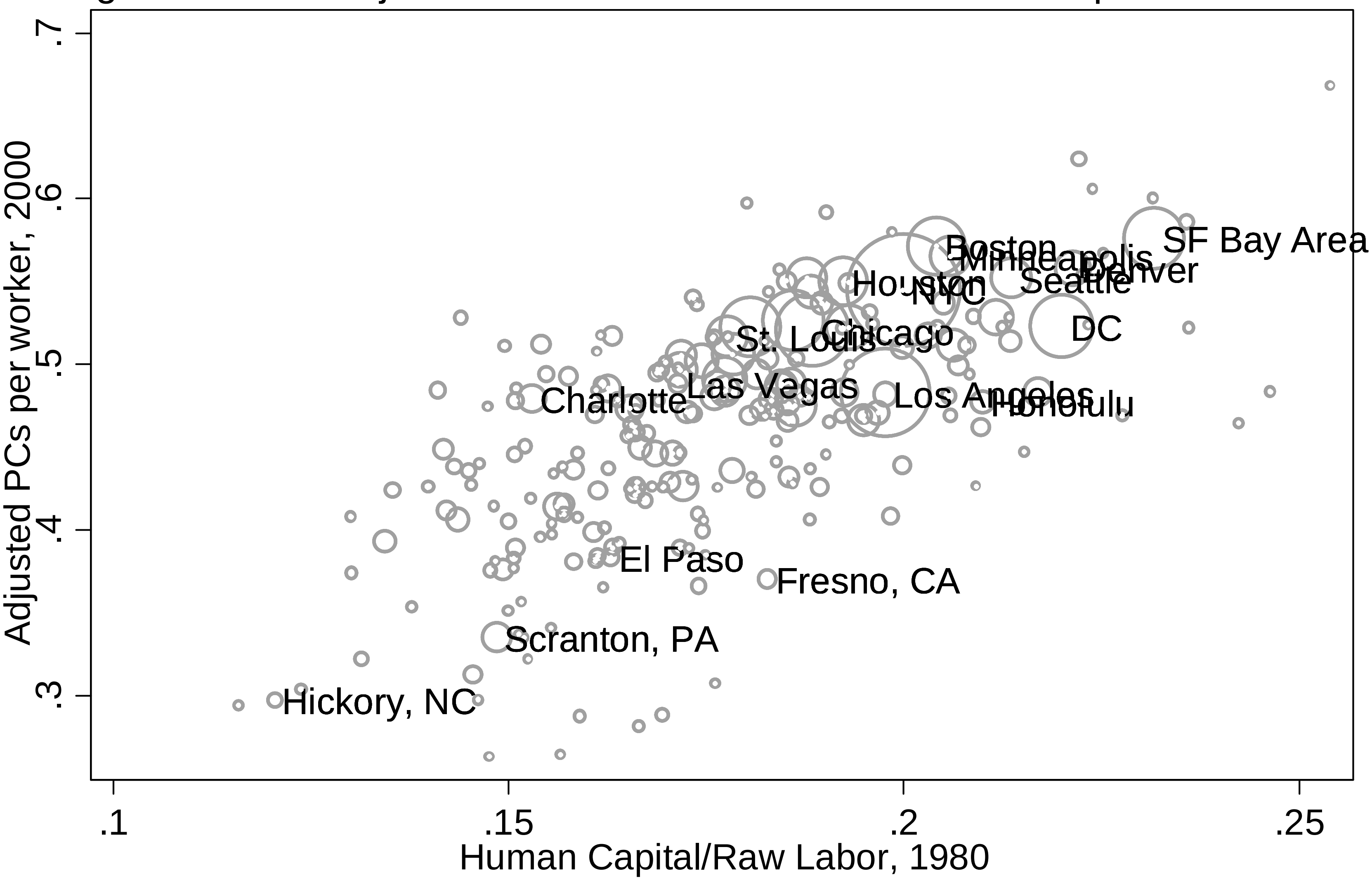


Figure 3. 2000 Adjusted* PCs/Worker vs. 1980 Human Capital/Raw Labor



*Adjusted for Size x Industry

Table 1. Descriptive Statistics

	1980		2000		Change 1980-2000	
	Mean	Stand Dev	Mean	Stand Dev	Mean	Stand Dev
	(1)	(2)	(3)	(4)	(5)	(6)
Adjusted Male-Female Wage Gap						
All Education Levels	**0.376**	**0.098**	**0.254**	**0.054**	**-0.123**	**0.082**
High School Dropouts	0.461	0.075	0.261	0.054	-0.200	0.068
High School Graduates	0.445	0.063	0.283	0.054	-0.162	0.041
>0 and <4 years college	0.380	0.053	0.248	0.047	-0.132	0.038
4 Years College	0.337	0.055	0.236	0.048	-0.102	0.052
Advanced Degree	0.257	0.068	0.239	0.054	-0.018	0.067
Adjusted College-HS Wage Gap	0.257	0.045	0.449	0.046	0.192	0.046
Human Capital/Raw Labor	0.188	0.021	0.231	0.023	0.043	0.014
Adjusted PCs/Worker			0.497	0.055		
Number of Metro Areas	230		230		230	

Notes: Raw data sources are the 1980 (Ruggles et al., 2010) and 2000 public use 5% censuses of population 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 human capital/raw labor consists of workers age 16-65 with positive potential work experience (age - years of education -6) and hours worked last year, and not residing in group quarters. This variable is close to an hours-weighted average years of schooling above 10 years (multiplied by the estimated return to schooling in 1980, 0.077), with an adjustment for the share of hours worked by females -- see text for details. 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 3 digit industry x employer size dummies. The descriptive statistics in this table are weighted by1980 population.

Table 2. Change in Male-Female Wage Gaps vs. Change in Schooling Wage Gaps, 1980-2000, Estimated by OLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Adj Coll-HS Wage Gap, 1980-2000	-0.231	-0.128	-0.163	-0.141	-0.207	-0.167	-0.151	
	(0.059)	(0.049)	(0.047)	(0.046)	(0.057)	(0.053)	(0.054)	
4 x ΔAdj (linear) Return to Schl, 1980-2000								-0.149
								(0.080)
Intercept	-0.078	-0.098	-0.066	-0.095	-0.083	-0.091	-0.094	-0.114
	(0.012)	(0.009)	(0.009)	(0.009)	(0.011)	(0.010)	(0.010)	(0.005)
Root MSE	0.054	0.052	0.046	0.051	0.050	0.049	0.049	0.049
R-squared	0.577	0.613	0.491	0.617	0.655	0.660	0.664	0.662
Observations	1,150	1,150	1,150	1,150	1,150	1,150	1,150	1,150
Controls								
Education Group?	Y	Y	Y	Y	Y	Y	Y	Y
Industry Mix x Broad Education?[1]	N	2 Manuf	Detailed (Individual)	2 Manuf +Index	2 Manuf +Index	2 Manuf +Index	2 Manuf +Index	2 Manuf +Index
State Effects?	N	N	N	N	Y	Y	Y	Y
City Controls?[2]	N	N	N	N	N	Y	Y	Y
F Emp Rate x Broad Ed?[3]	N	N	N	N	N	N	Y	Y

Data Source: 5% Public-use 1980 (Ruggles et al., 2010) and 2000 public use censuses of population, which are aggregated to 230 metropolitan areas, and, for the dependent variable, x 5 education groups (high school dropouts, graduates, some college <4 years, 4 years college, and advanced degree) that are the units of observation in the regressions. Sample consists of workers age 16-65 with positive potential work experience (age - years of education -6) and hours worked last year, not residing in group quarters,who are currently employed, with positive wage earnings but zero business and farm earnings and not currently enrolled in school. Dependent variable is the gap between the average ln hourly wage of men and women with the same broad education level, adjusted in gender x education (x year) specific regressions for a quartic in potential experience, linear education (for dropouts, some college, and advanced degree) and dummies for black, Hispanic, foreign-born, and born after 1950 (with latter also interacted with years education for the same three groups). Independent variable is the average of (simililarly adjusted) college-high school wage gaps for men and women. All regressions in table weighted by 1980 population. Standard errors, in parentheses under slope estimates, are computed to be robust to arbitrary forms of heteroskedasticity and error correlation within metropolitan area. [1]Columns (2) and (4)-(8) control for the share of employment in non-durable and durable manufacturing their interactions with a dummy for being in the "some college" or lower broad education group. Column (3) adds to the indvidual-level wage adjustments controls for detailed census of population industries that corresponds roughly to the level of industry detail in 1980. Columns (4) and higher control for a female demand "Index" which is the female share of employment obtained by averaging national female employment shares by detailed industry using local employment by industry as weights. This index is constructed separately for "college equivalents" (which is is used as the control for broad education categories four years college and advanced degrees) and "high school equivalents" (which is is used as the control for broad education categories dropouts, high school and some college) but entered as a single control variable. [2]City controls are share black, Hispanic, and foreign-born; and the unemployment rate and the natural log of the labor force. [3]Female employment rates entered separately for those with some college or less and four years college or more.

Table 3. Change in Wage Gaps on Human Capital/Raw Labor, 1980

	(1)	(2)	(3)	(4)	(5)
A. Change in Adjusted Male-Female Wage Gap, 1980-2000					
Human Capital/	-0.528	-0.804	-0.891	-1.048	-0.932
Raw Labor, 1980	(0.142)	(0.177)	(0.252)	(0.316)	(0.315)
R-squared	0.578	0.630	0.661	0.666	0.667
B. Change in Adjusted College-High School Wage Gap, 1980-2000					
Human Capital/	0.993	1.248	1.258	1.267	1.287
Raw Labor, 1980	(0.276)	(0.381)	(0.289)	(0.351)	(0.389)
R-squared	0.207	0.274	0.588	0.603	0.604
Observations	1,150	1,150	1,150	1,150	1,150
Controls					
Education Group?	Y	Y	Y	Y	Y
Industry Mix	N	2 Manuf	2 Manuf	2 Manuf	2 Manuf
x Broad Education?[1]		+Index	+Index	+Index	+Index
State Effects?	N	N	Y	Y	Y
City Controls?[2]	N	N	N	Y	Y
F Emp Rate x Broad Ed?[3]	N	N	N	N	Y

Data Source: 5% Public-use 1980 (Ruggles et al., 2010) and 2000 Censuses of Population, which are aggregated to 230 metropolitan areas (and, for the dependent variable in panel A, x 5 education groups -- high school dropouts, graduates, some college <4 years, 4 years college, and advanced degree). Sample for constructing independent variable consists of workers age 16-65 with positive potential work experience (age - years of education -6) and hours worked last year, not residing in group quarters. "Human capital" is the sum of the interaction of hours worked with years of education beyond 10 times 0.077, and "raw labor" is 1.423 times the sum of male hours worked plus the sum of female hours worked. The wage sample is the subsample who are currently employed, with positive wage earnings but zero business and farm earnings and not currently enrolled in school. Dependent variable in panel A is the (change in the) gap between the average ln hourly wage of men and women with the same broad education level, where the adjustment are gender x education (x year) specific regressions on a quartic in potential experience, linear education (for dropouts, some college, and advanced degree) and dummies for black, Hispanic, foreign-born, and born after 1950 (with latter also interacted with years education for the same three groups). Dependent variable in panel B is the average of (simililarly adjusted change in the) college-high school wage gaps for men and women. All regressions in table weighted by 1980 population. Standard errors, in parentheses under slope estimates, are computed to be robust to arbitrary forms of heteroskedasticity and error correlation within metropolitan area. [1]Columns (2)-(5) control for the share of employment in non-durable and durable manufacturing their interactions with a dummy for being in the "some college" or lower broad education group, and for a female demand "Index" which is the female share of employment obtained by averaging national female employment shares by detailed industry using local employment by industry as weights. This index is constructed separately for "college equivalents" (which is is used as the control for broad education categories four years college and advanced degrees) and "high school equivalents" (which is is used as the control for broad education categories dropouts, high school and some college) but entered as a single control variable. [2]City controls are share black, Hispanic, and foreign-born; and the unemployment rate and the natural log of the labor force. [3]Female employment rates entered separately for those with some college or less and four years college or more.

Table 4a. Change in (Adjusted) Male-Female Wage Gaps, 1980-2000, vs. Personal Computer Adoption Intensity

	(1)	(2)	(3)	(4)	(5)
			A. Ordinary Least Squares		
Personal Computers/	-0.204	-0.207	-0.157	-0.115	-0.089
Worker, 2000	(0.048)	(0.041)	(0.052)	(0.061)	(0.066)
Change in Hum Cap/	0.821	0.417	0.032	-0.192	-0.355
RL, 1980-2000	(0.180)	(0.172)	(0.338)	(0.365)	(0.408)
Root MSE	0.053	0.051	0.050	0.049	0.049
R-squared	0.591	0.626	0.654	0.659	0.663
			B. Instrumental Variables		
Personal Computers/	-0.239	-0.363	-0.367	-0.482	-0.440
Worker, 2000	(0.063)	(0.081)	(0.095)	(0.152)	(0.158)
Change in Hum Cap/	0.845	0.547	0.589	0.371	0.178
RL, 1980-2000	(0.188)	(0.203)	(0.367)	(0.466)	(0.479)
Root MSE	0.053	0.051	0.050	0.051	0.050
Observations	1,150	1,150	1,150	1,150	1,150
First Stage F-Stat	136.5	107.9	93.8	74.1	63.1
p-value	0.000	0.000	0.000	0.000	0.000
Controls					
Education Group?	Y	Y	Y	Y	Y
Industry Mix	N	2 Manuf	2 Manuf	2 Manuf	2 Manuf
x Broad Education?[1]		+Index	+Index	+Index	+Index
State Effects?	N	N	Y	Y	Y
City Controls?[2]	N	N	N	Y	Y
F Emp Rate x Broad Ed?[3]	N	N	N	N	Y

Data Source: Dependent variable and human capital -- 5% Public-use 1980(Ruggles et al., 2010) and 2000 Censuses of Population, which are aggregated to 230 metropolitan areas, and, for the dependent variable, x 5 education groups (high school dropouts, graduates, some college <4 years, 4 years college, and advanced degree) that are the units of observation in the regressions. Sample used to compute human capital/raw labor, consists of workers age 16-65 with positive potential work experience (age - years of education -6) and hours worked last year, and not residing in group quarters. "Human capital" is the sum of the interaction of hours worked with years of education beyond 10 times 0.077, and "raw labor" is 1423 times the sum of male hours worked plus the sum of female hours worked. The wage sample is the subsample who are currently employed, with positive wage earnings but zero business and farm earnings and not currently enrolled in school; dependent variable is the change in the adjusted wage gap between the average ln hourly wage of men and women with the same broad education level, where the adjustment are gender x education (x year) specific regressions on a quartic in potential experience, linear education (for dropouts, some college, and advanced degree) and dummies for black, Hispanic, foreign-born, and born after 1950 (with latter also interacted with years education for the same three groups). PCs per worker computed from stacked 2000 and 2002 marketing surveys by Harte Hanks, which are regression adjusted for 3 digit industry x employer size dummies. Instrument is 1980 human capital/raw labor. All regressions in table weighted by 1980 population. Standard errors, in parentheses under slope estimates, are computed to be robust to arbitrary forms of heteroskedasticity and error correlation within metropolitan area. [1]Columns (2)-(5) control for the share of employment in non-durable and durable manufacturing their interactions with a dummy for being in the "some college" or lower broad education group, and for a female demand "Index" which is the female share of employment obtained by averaging national female employment shares by detailed industry using local employment by industry as weights. This index is constructed separately for "college equivalents" (which is is used as the control for broad education categories four years college and advanced degrees) and "high school equivalents" (which is is used as the control for broad education categories dropouts, high school and some college) but entered as a single control variable. [2]City controls are share black, Hispanic, and foreign-born; and the unemployment rate and the natural log of the labor force. [3]Female employment rates entered separately for those with some college or less and four years college or more.

Table 4b. Change in Adjusted College-High School Wage Gaps, 1980-2000, vs. Personal Computers Adoption Intensity

	(1)	(2)	(3)	(4)	(5)
			A. Ordinary Least Squares		
Personal Computers/	0.306	0.256	0.246	0.210	0.204
Worker, 2000	(0.089)	(0.088)	(0.063)	(0.062)	(0.063)
Change in Hum Cap/	-1.242	-1.117	0.748	0.850	0.938
RL, 1980-2000	(0.258)	(0.277)	(0.525)	(0.538)	(0.520)
Root MSE	0.041	0.040	0.030	0.030	0.030
R-squared	0.227	0.253	0.584	0.598	0.602
			B. Instrumental Variables		
Personal Computers/	0.463	0.526	0.467	0.544	0.567
Worker, 2000	(0.139)	(0.185)	(0.119)	(0.148)	(0.175)
Change in Hum Cap/	-1.349	-1.341	0.160	0.338	0.387
RL, 1980-2000	(0.288)	(0.346)	(0.544)	(0.521)	(0.525)
Root MSE	0.041	0.042	0.032	0.032	0.032
Observations	1,150	1,150	1,150	1,150	1,150
First Stage F-Stat	136.5	107.9	93.8	74.1	63.1
p-value	0.000	0.000	0.000	0.000	0.000
Controls					
Education Group?	Y	Y	Y	Y	Y
Industry Mix	N	2 Manuf	2 Manuf	2 Manuf	2 Manuf
x Broad Education?[1]		+Index	+Index	+Index	+Index
State Effects?	N	N	Y	Y	Y
City Controls?[2]	N	N	N	Y	Y
F Emp Rate x Broad Ed?[3]	N	N	N	N	Y

Data Source: Dependent variable and human capital -- 5% Public-use 1980 (Ruggles et al., 2010) and 2000 Censuses of Population, which are aggregated to 230 metropolitan areas. Sample used to compute human capital/raw labor, consists of workers age 16-65 with positive potential work experience (age - years of education -6) and hours worked last year, and not residing in group quarters. "Human capital" is the sum of the interaction of hours worked with years of education beyond 10 times 0.077, and "raw labor" is 1423 times the sum of male hours worked plus the sum of female hours worked. The wage sample is the subsample who are currently employed, with positive wage earnings but zero business and farm earnings and not currently enrolled in school; dependent variable is the change in the average of male and female ln hourly wage gaps between college and high school workers, where the adjustments are gender x education (x year) specific regressions on a quartic in potential experience, linear education (for dropouts, some college, and advanced degree) and dummies for black, Hispanic, foreign-born, and born after 1950 (with latter also interacted with years education for the same three groups). PCs per worker computed from stacked 2000 and 2002 marketing surveys by Harte Hanks, which are regression adjusted for 3 digit industry x employer size dummies. Instrument is 1980 human capital/raw labor. All regressions in table weighted by 1980 population. Standard errors, in parentheses under slope estimates, are computed to be robust to arbitrary forms of heteroskedasticity and error correlation within metropolitan area. [1]Columns (2)-(5) control for the share of employment in non-durable and durable manufacturing their interactions with a dummy for being in the "some college" or lower broad education group, and for a female demand "Index" which is the female share of employment obtained by averaging national female employment shares by detailed industry using local employment by industry as weights. This index is constructed separately for "college equivalents" (which is is used as the control for broad education categories four years college and advanced degrees) and "high school equivalents" (which is is used as the control for broad education categories dropouts, high school and some college) but entered as a single control variable. [2]City controls are share black, Hispanic, and foreign-born; and the unemployment rate and the natural log of the labor force. [3]Female employment rates entered separately for those with some college or less and four years college or more.

Table 5. Male-Female Wage Gaps vs. College-High School Wage Gaps, Estimated by Instrumental Variables

	(1)	(2)	(3)	(4)	(5)
Δ Adj Coll-HS Wage	-0.532	-0.644	-0.708	-0.827	-0.724
Gap, 1980-2000	(0.206)	(0.288)	(0.279)	(0.383)	(0.365)
Intercept	-0.020	0.001	0.014	0.036	0.017
	(0.038)	(0.054)	(0.053)	(0.073)	(0.069)
Root MSE	0.0555	0.0557	0.0523	0.0535	0.0522
R-squared	0.549	0.549	0.617	0.601	0.620
Observations	1,150	1,150	1,150	1,150	1,150
Controls					
Education Group?	Y	Y	Y	Y	Y
Industry Mix	N	2 Manuf	2 Manuf	2 Manuf	2 Manuf
x Broad Education?[1]		+Index	+Index	+Index	+Index
State Effects?	N	N	Y	Y	Y
City Controls?[2]	N	N	N	Y	Y
F Emp Rate x Broad Ed?[3]	N	N	N	N	Y

Data Source: 5% Public-use 1980 (Ruggles et al., 2010) and 2000 public use censuses of population, which are aggregated to 230 metropolitan areas, and, for the dependent variable, x 5 education groups (high school dropouts, graduates, some college <4 years, 4 years college, and advanced degree) that are the units of observation in the regressions. Sample consists of workers age 16-65 with positive potential work experience (age - years of education -6) and hours worked last year, not residing in group quarters,who are currently employed, with positive wage earnings but zero business and farm earnings and not currently enrolled in school. Dependent variable is the gap between the adjusted average ln hourly wage of men and women with the same broad education level, where the adjusted wage comes from gender x education (x year) specific regressions of ln(wage) on a quartic in potential experience, linear education (for dropouts, some college, and advanced degree) and dummies for black, Hispanic, foreign-born, and born after 1950 (with latter also interacted with years education for the same three groups). Independent variable is the average of (simililarly adjusted) college-high school wage gaps for men and women. The instrument is 1980 "human capital/raw labor"; first stage and further description of this variable are found in the notes to tables 3a and 4a. All regressions in table weighted by 1980 population. Standard errors, in parentheses under slope estimates, are computed to be robust to arbitrary forms of heteroskedasticity and error correlation within metropolitan area. [1]Columns (2)-(5) control for the share of employment in non-durable and durable manufacturing their interactions with a dummy for being in the "some college" or lower broad education group, and for a female demand "Index" which is the female share of employment obtained by averaging national female employment shares by detailed industry using local employment by industry as weights. This index is constructed separately for "college equivalents" (which is is used as the control for broad education categories four years college and advanced degrees) and "high school equivalents" (which is is used as the control for broad education categories dropouts, high school and some college) but entered as a single control variable. [2]City controls are share black, Hispanic, and foreign-born; and the unemployment rate and the natural log of the labor force. [3]Female employment rates entered separately for those with some college or less and four years college or more.

Table 6. Change in Male-Female Wage Gap, 1980-2000, Correcting for Selection

					Adjusted for Inverse Mills Ratio	
					Nationally	*By MSA*
	(1)	(2)	(3)	(4)	(5)	(6)
Female Subsample:		Predicted Emp. Rates High[1]	Nonminority[2] never married w/NO kids<6	Nonminority[2] Aged 25-44 WITH kids<6		
Male Subsample:			Nonminority[2]	Nonminority[2] Aged 25-44		
	A. Change in Adjusted Male-Female Wage Gap, 1980-2000, OLS					
Δ Adj Coll-HS Wage Gap, 1980-2000	-0.134	-0.079	-0.332	-0.125	-0.170	-0.419
	(0.066)	(0.075)	(0.105)	(0.134)	(0.068)	(0.298)
Root MSE	0.047	0.074	0.098	0.119	0.049	0.309
R-squared	0.689	0.521	0.357	0.216	0.898	0.239
	B. Change in Adjusted Male-Female Wage Gap, 1980-2000, IV					
Δ Adj Coll-HS Wage Gap, 1980-2000	-0.575	-0.411	-1.046	-0.929	-0.451	-0.625
	(0.290)	(0.251)	(0.361)	(0.413)	(0.258)	(0.717)
Root MSE	0.048	0.074	0.100	0.121	0.050	0.309
Observations	905	905	905	905	905	905
Controls						
Education Group?	Y	Y	Y	Y	Y	Y
Industry Mix	2 Manuf	2 Manuf	2 Manuf	2 Manuf	2 Manuf	2 Manuf
x Broad Education?[3]	+Index	+Index	+Index	+Index	+Index	+Index
State Effects?	Y	Y	Y	Y	Y	Y
City Controls?[4]	Y	Y	Y	Y	Y	Y

Data Source: 5% Public-use 1980 (Ruggles et al., 2010) and 2000 public use censuses of population, w hich are aggregated to 230 metropolitan areas, and, for the dependent variable, x 5 education groups (high school dropouts, graduates, some college <4 years, 4 years college, and advanced degree) that are the units of observation in the regressions. Sample consists of w orkers age 16-65 w ith positive potential w ork experience (age - years of education-6) and hours w orked last year, not residing in group quarters,w ho are currently employed, w ith positive w age earnings but zero business and farm earnings and not currently enrolled in school. Dependent variable is the gap betw een the average ln hourly w age of men and w omen w ith the same broad education level, adjusted in gender x education (x year) specific regressions for a quartic in potential experience, linear education (for dropouts, some college, and advanced degree) and dummies for black, Hispanic, foreign-born, and born after 1950 (w ith latter also interacted w ith years education for the same three groups). Independent variable is the average of (simililarly adjusted) college-high school w age gaps for men and w omen. All regressions in table w eighted by 1980 population. Standard errors, in parentheses under slope estimates, are computed to be robust to arbitrary forms of heteroskedasticity and error correlation w ithin metropolitan area. The instrument, used in panels B, is 1980 "human capital/raw labor," w hich is discussed in notes to previous tables. [1]Women w ith characteristics associated w ith a greater than 60 chance of w orking in the average metropolitan area (as of 1980). To determine this, a probit for being in the w age sample (among w omen age 16-65 w ith positive potential w ork experience not residing in group quarters) on the same variables as the w age adjustment plus dummies for marital status interacted w ith a dummy for children under six, w as separately estimated by gender and education using the 1980 data. The predicted values, p, from this probit (evaluated at the average of the metropolitan area effects) w as computed and w omen w ith p>0.6 w ere retained. [2]Non-Hispanic native-born w hites. [3]The share of employment in non-durable and durable manufacturing and their interactions w ith a dummy for being in the "some college" or low er broad education group, and a female demand "Index" w hich is the female share of employment obtained by averaging national female employment shares by detailed industry using local employment by industry as w eights. The index is constructed separately for "college equivalents" (w hich is is used as the control for broad education categories four years college and advanced degrees) and "high school equivalents" (w hich is is used as the control for broad education categories dropouts, high school and some college) [4]City controls are share black, Hispanic, and foreign-born; and the unemployment rate and the natural log of the labor force.

Table 7. Change in Male-Female Wage Gap by Period, Large MSA subsample

Analysis Period:	1970-1980	1980-1990	1980-2000
	(1)	(2)	(3)
A. Versus Change in College-High School Wage Gap			
Change in College-High School Wage Gap	0.126	-0.250	-0.198
	(0.105)	(0.061)	(0.071)
R-squared	0.409	0.582	0.745
B. Versus 1980 Human Capital/Raw Labor			
Human Capital/ Raw Labor, 1980	-0.377	-1.380	-1.088
	(0.409)	(0.295)	(0.436)
R-squared	0.408	0.592	0.749
Observations	685	685	685
Wage Methods:[1]	1970	1970	1980-2000
Controls			
Education Group?	Y	Y	Y
Industry Mix x Broad Education?[2]	2 Manuf +Index	2 Manuf +Index	2 Manuf +Index
State Effects?	Y	Y	Y
City Controls?[3]	Y	Y	Y

Data Source: 1970 public-use "county group," 1980 5% public use, (both Ruggles et al., 2010) and 1990 and 2000 5% public use censuses of population, w hich are aggregated to 137 metropolitan areas x 5 education groups (high school dropouts, graduates, some college <4 years, 4 years college, and advanced degree) that are the units of observation in the regressions. Sample for human capital/raw labor consists of w orkers age 16-65 w ith positive potential w ork experience (age - years of education -6) and hours w orked last year, not residing in group quarters; w age sample further limited to those w ho are currently employed, w ith positive w age earnings but zero business and farm earnings and not currently enrolled in school. Dependent variable is the gap betw een the average ln hourly w age of men and w omen w ith the same broad education level, adjusted in gender x education (x year) specific regressions for a quartic in potential experience, linear education (for dropouts, some college, and advanced degree) and dummies for black, Hispanic, foreign-born, and born after 1950 (w ith latter also interacted w ith years education for the same three groups). Independent variable in Panel A is the average of (simililarly adjusted) college-high school w age gaps for men and w omen. Independent variable in Panels B is "human capital" -- the sum of the interaction of annual hours w orked w ith years of education beyond 10 times 0.077 -- divided by "raw labor" --- 1.423 times the sum of male annual hours w orked plus the sum of female hours w orked. All regressions in table w eighted by 1980 population. Standard errors, in parentheses under slope estimates, are computed to be robust to arbitrary forms of heteroskedasticity and error correlation w ithin metropolitan area. [1]"1970" w age methods employ categorical versions of "hours last w eek" and "w eeks last year" available in the 1970 Census, interpolated to continuous hours and w eeks (using means in 1980 census data) to compute annual hours w orked. Column (3), like the other tables, uses reports of (continuous) "usual hours per w eek" and "w eeks last year" to compute annual hours w orked. [2]The share of employment in non-durable and durable manufacturing and their interactions w ith a dummy for being in the "some college" or low er broad education group, and a female demand "Index" w hich is the female share of employment obtained by averaging national female employment shares by detailed industry using local employment by industry as w eights. The index is constructed separately for "college equivalents" (w hich is is used as the control for broad education categories four years college and advanced degrees) and "high school equivalents" (w hich is is used as the control for broad education categories dropouts, high school and some college) [3]City controls are share black, Hispanic, and foreign-born; and the unemployment rate and the natural log of the labor force.