Women's Economic Progress and Technological Change

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Abstract

This paper attempts to assess the power of technological change on women's wage progress from 1982 to 1996 using a simple supply and demand framework. I distinguish two types of technological change: skill-biased and sex-biased technological change; the latter predominantly favors women and is represented by the pill. My main conclusion is that the pill has little impact on females' wages when compared to skill-biased technological change, yet skill-biased technological change cannot explain the gender premium because it benefits men and women similarly. I also find that the primary impact of the pill is to raise labor force participation, encouraging high-tech sector employment is secondary. I find evidence that relative skill supply weakly induces innovation.

Keywords: directed technological change, sector allocation, patent innovation, contraception

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1 Introduction

Can technological change explain the wage progress of women? Between 1967 and 2001, females' wages rose 46 percent or at an astounding rate of 1.31 percent per annum. Relative wages between women and men also rose considerably. The average wage of women relative to the average wage of men (gender premium) increased by about 27 percent. Meanwhile, relative labor demand shifts between and within industries showed remarkable reallocation patterns for female labor. Specifically, the fraction of women working in skill-intensive industries grew about 38-41 percent; the growth was sharpest between late 60s and 70s[1]. Women also made up over half of employment in these industries since the 80s.

Despite relative labor demand shifts that indicate industries that are skill-intensive tend to demand more female labor, the impact of skill-biased technological change on the gender wage trend is unclear. On the one hand, studies showed that skill-biased technological change was a major factor of the rising gender premium (e.g. Bound and Johnson (1992) and Allen (2001)). On the other hand, some studies hypothesized that men have an absolute advantage in skill, an increase in skill prices inflates male wage, and the gender premium must fall (e.g. Card and DiNardo (2001)). These studies concluded that skill-biased technological change cannot reconcile with the gender premium and suggest one should look into sex-specific factors.

But technological change can be sex-specific. I define *sex-biased* technological change as one that disproportionately favors women's productivity. One example is the advance in female oral contraception, which let women manipulate the timing of fertility to advance their career.[2] Using differential effect of legal changes for the dissemination of the pill by state, Goldin and Katz (2002) argued that the pill has promoted young and single female professional development as it reduces the penalty of pre-marital sex.[3] However, pill usage data show that for women of age 25-29, when professional education acquisition mostly occurs, pill users and pill-free women had similar school attendance rate. Yet when compared with pill-free women, more pill-users worked in professional industries and had higher earnings. It appears that while some women use the pill to pursue advanced education as hypothesized by Katz and Goldin (2002), others may simply use the pill and work, rely on job-training or make greater use of their labor qualities (e.g. communication or team-building skills) that are rewarded in skill-intensive industries. So, the pill may help women utilize their ability or general-skill more fully.

[1] In what follows, I use skill-intensive industries and the high-tech sector interchangeably.

[2] Its diffusion began in 1960 through early 1970s, a period after which matches the sharp rise in women's participation in skilled sectors more closely than the period of diffusion of the computer or IT. One might argue that computers are sex-biased because many workers who use computers are women. Utilizing the October CPS (1984, 1989, 1993), Autor et. al (1998) showed that the fraction of men using computer at work approached that of women.

[3] Bailey (2005) used the same natural experiment proposed by Goldin and Katz (2002) to study the effect of the pill on women's labor force participation. Nonetheless, the existing literature examines the impact of the pill on professional development and labor force participation in isolation, this paper evaluates the power of each impact.

Another issue is concerned with how technological change affects the gender premium. Despite existing literature that studies the direct effect of technological change, how capital deepening or R&D expenditure affects the gender premium remains unclear. The microfounded explanation was given by Galor and Weil (1996). According to Galor and Weil, women have a comparative advantage in mental-labor. An increase in relative skill reward due to capital deepening raises the value of mental-labor; so the gender premium goes up.[4] In this paper, I consider skill-biased technological change influences workers' wage through its positive impact on relative skill reward, and the pill directly increases females' wage through enhancing productive efficiency. However, both types of technological change favor the allocation of workers into skill-intensive industries, generating ambiguous effects on relative skill reward that determines the direction of the feedback effect on the supply side.[5] On the one hand, it creates some amount of technological change in favor of skill, and the usual substitution effect reduces relative skill reward. This is the so-called 'weak induced-bias' technological change (Acemoglu, 2001). On the other hand, if the elasticity of substitution between high and low-skill workers is sufficiently large, the induced-bias in technology can overcome the substitution effect and raise the relative skill reward. These interactions complicate the wage response of technological change, making the issue difficult to be addressed without an equilibrium framework.

The objective of this paper is to examine women's wage progress in a simple demand and supply framework that considers both types of technological change. It predicts women's progress even men have absolute advantage in all skills. It also provides a structure to the empirical analysis of technological change. My main conclusion is that technological change raises females' wages primarily through skill-biased technological change, not the pill; yet skill-biased technological change cannot explain the gender premium because it has similar impact on men's and women's wages. The result of sex-neutrality may reflect skill-biased technological change has become diffused between men and women. I also find that the primary impact of the pill is to raise labor force participation, encouraging high-tech sector employment is secondary. I find evidence that relative skill supply weakly induces innovation, with the elasticity of substitution between skilled and unskilled workers to be 1.84, higher than the existing estimates obtained without accounting for the supply side.[6]

The supply and demand framework synthesizes Roy's (1951) sector choice model and Acemoglu's (2001) directed (skill-biased) technical change model. The economy is populated by workers with heterogeneous skill-mix on cognitive and physical ability and it has two sectors: high-tech and low-tech. The pill triggers a sequence of events. By helping women utilize their ability more fully, the pill leads more women to sort themselves into sectors that favor women's abilities, i.e. mental-labor rather than physical-labor. But the

[4] Welch (2001) also had a similar idea, but did not explore the source of the higher skill price.

[5] Bartel and Sicherman (1999) found that the wage premium associated with technological change is purely due to the sorting of more 'skilled' workers into those industries. 'Skilled' was referred to innate ability or other unobserved characteristics that are not perfectly correlated with education.

[6] See, for example, Bound and Johnson (1992), Katz and Murphy (1992), Krusell et al.(1997), Autor et al. (1998), and Heckman et al. (1998). These studies focused on college premiums and found estimates around 1.4-1.6.

impact of the pill does not stop here. The composition effect propagates to the macro economy. As more women ushered into the high-tech sector, the relative share of skilled workers expands. Initially, this dampens wage premiums favoring the high-tech sector (relative skill reward), i.e. the 70s phenomenon. But profit incentives lead firms to direct innovation towards technologies in the high-tech sector, creating the second tier of sorting.[7] The induced technological change can push up relative skill reward.[8] The higher relative skill reward creates a feedback effect that encourages even more workers (men and women) to enter the sector. This creates a dual of expanding the market size for skilled and rising relative skill reward. As men and women become more similar in productivity, more workers entering the high-tech sector raises the gender premium. Thus, the model can rationalize women's wage progress.

How far can one go towards explaining these interactions empirically using the simple supply and demand framework? First, I consider patent to be the source of innovation. I use quality-adjusted patent measures instead of patent counts because innovations vary enormously in their qualitative impacts technologically or economically and these differences cannot be captured by count data.[9] Second, rather than using time series data, I construct state-level datasets. States are a more appropriate level of aggregation because technology-based firms are typically geographically localized, such as those in California and Massachusetts. Even if there is a trend towards more high-tech production, such a transition may not occur uniformly throughout the country. Thus, different states may move towards new technology at different speeds; and state-level data provide a source of variation in skill-biased technological change. On the factor-mobility ground, if free mobility makes the United States a single labor market, where no relative employment or factor price differences across state-level labor markets occurs, using state-level data could be problematic. But many studies find significant wage and employment differences across state-level labor markets.[10]

Following Katz and Murphy (1992), I examine employment distributions by industries. I stratify all industries into high and low-tech sectors based on workers' skills, instead of using the rate of technological change as in convention studies.[11] Typical interindustry wage differential and technological change studies consider only manufacturing industries where good measures of technological change are available.[12] However, focusing only on manufacturing excludes industries such as medical, professional, and business services that have made up the major females' employment trend since 1970s. Moreover, insofar as physical and human capital are complementary, industries that use more physical capital also demand more skilled workers. Finally, I use an adjusted two-stage-least-square (2SLS)

[7] Innovation can also be driven by other means such as 'general-purpose technologies' introduced by Bresnahan and Trajtenberg (1995).

[8] Where the elasticity of subsititution is sufficiently large, what Acemoglu referred to as 'strong induced-bias hypothesis', the long-run relative demand curve can slope up.

[9] See, for example, Schankerman and Pakes (1984), and Griliches (1990).

[10] See, for example, Topel (1994), Moretti (2000), and Dahl (2002).

[11] See, for example, Bartel and Sicherman (1999).

[12] Griliches (1994) emphasized that measurement of technological change outside manufacturing industry is problematic. However, even within the manufacturing sector, there is no perfect measure; see Bartel and Sicherman (1999) for a detail study.

method to estimate the equilibrium model.[13] Adjustment is made to capture endogenous sector allocation. As demonstrated convincingly in Bartel and Sicherman (1999), sector allocation is important in shaping industrial relative skill reward.

The paper is organized as follows. Section 2 presents trends in women's wages, gives examples on sex-biased technological change, and documents pill-usage data. Section 3 outlines the simple theoretical framework and derive key empirical predictions. Predictions on employment and wages are not transparent, when workers with heterogeneous abilities are allowed to make sector choice. I show that model predictions hinge on the ability distribution being *bivariate normal.* One interesting prediction of the model is that men is endogenously more productive than women. Information on datasets and technology sector definition are described in section 4. Section 5 contains empirical analyses on relative skill reward, relative skill supply, and wages. Section 6 concludes.

2 Some Facts

Section 2.1 presents facts on evolution in females' wages, the gender premium, and female employment. Section 2.2 presents other examples of sex-biased technological change. Section 2.3 presents facts on some labor market characteristics between pill-users and pill-free women.

2.1 Women's Progress

The key facts from this section are (1) females' wages grew steadily from late 60s onwards, about twice as much as the female to male wage ratio, (2) the fraction of women working in skill-intensive industries grew over time, rising precipitously during late 60s and 70s, and (3) women have become the dominant gender in the high-tech sector since the 80s.

The main data used in this section come from the March Current Population Survey (CPS, 1968-2002). These data provide earnings and employment information. From the data I create two samples for workers aged 25-40: a wage sample (2.1.1) and a count sample (2.1.2). Sample selection follows Katz and Murphy (1992) and is described in the Data Appendix. I also use the IPUMS (1950-1960) to document relative labor demand shifts to check whether dramatic shifts had indeed occurred since late 1960s.

2.1.1 Wages

The period 1967-2001 witnessed a sharp increase in females' wages. The indexed wage displayed in figure 1 shows that females' wages grew steadily overtime. With respect to 1967, the year 2001 saw females' wages surged about 46 percent, or 1.33 percent per annum.

[13] I do not take Heckmand and Sedlacek's approach (1985) because they were concerned with estimating unmeasured sector-specific productive attributes at a micro-level using a Box-Cox model. Similar to existing literature that analyzes movements of college premium, I choose the simpler empirical macro-level analysis.

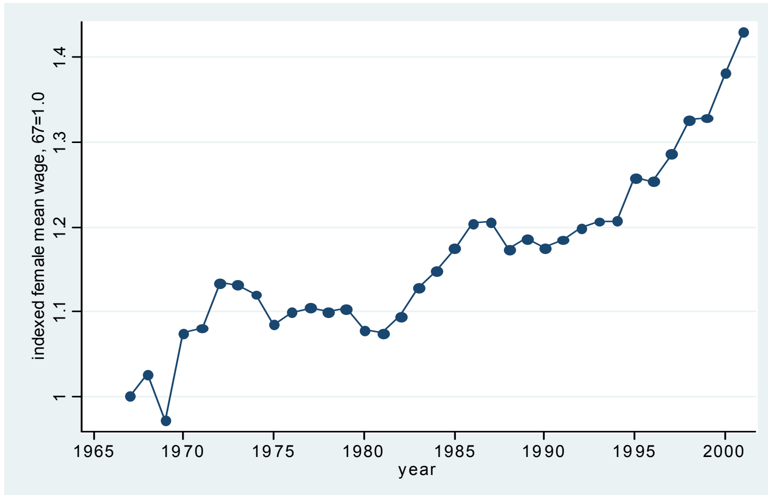

Figure 1. Indexed Mean Wage for Women (age 25-40)

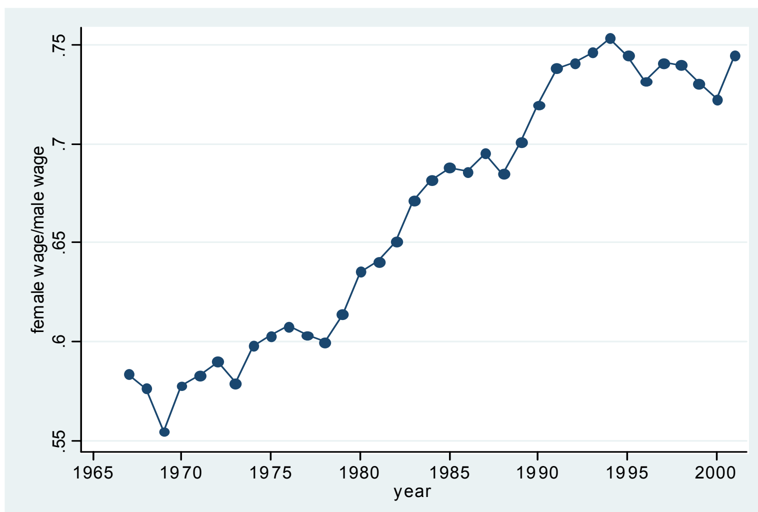

Figure 2. The Ratio of Mean Female Wage to Mean Male Wage (age 25-40)

Figure 2 illustrates the movements of the female to male wage ratio. The trend took off since late 60s and slowed down after early 90s. The wage ratio rose approximately 27 percent between 1967 and 2001. In particular, the ratio climbed 1.37 percent each year from 0.5793 in 1973 to reach a ratio of 0.7539 in 1994. This trend differs from the conventional trend that summarizes workers of age 18-65. In this group, the wage ratio rose about 19.7 percent between 1967-2001, about 30 percent less than the young-worker sample.

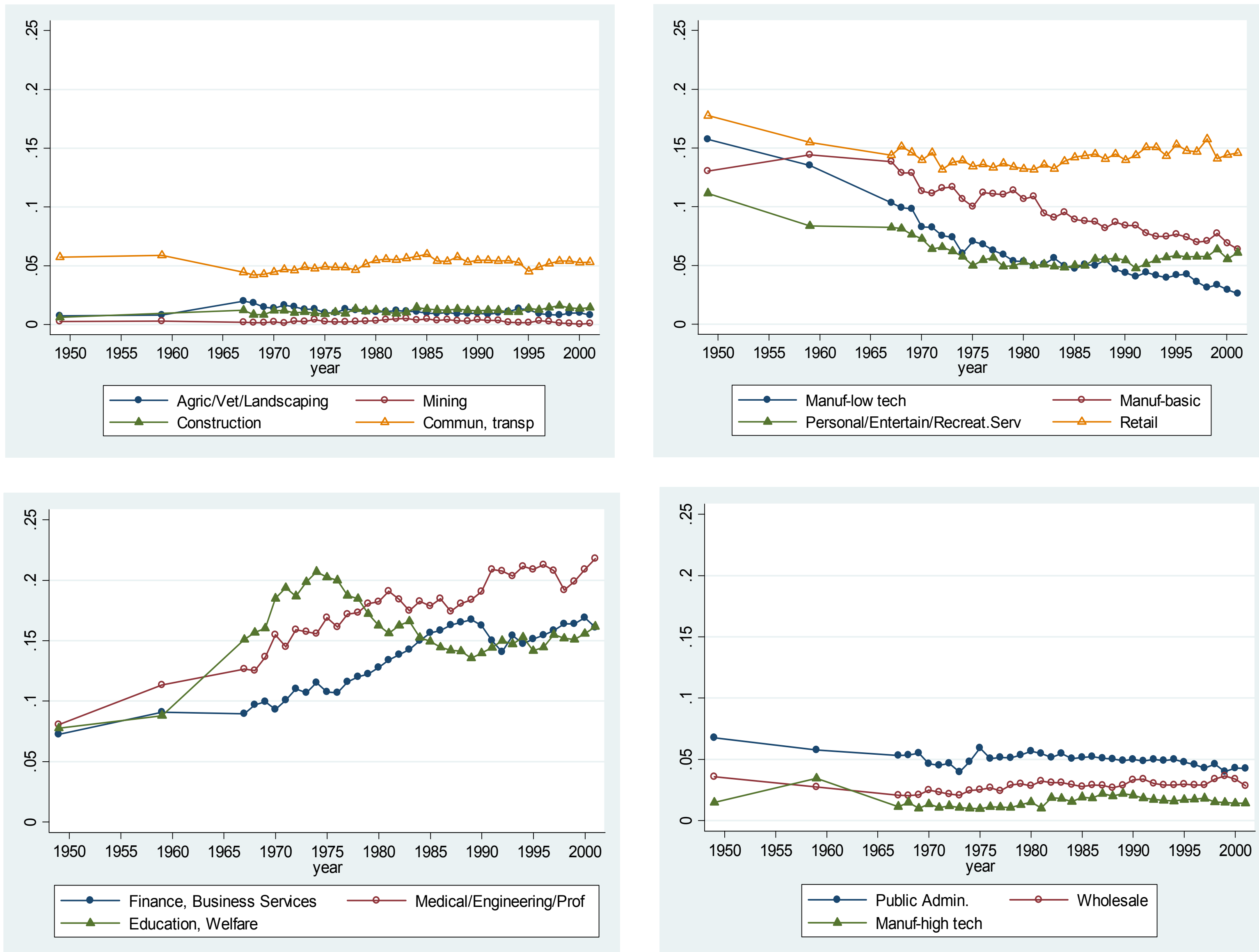

Figure 3. Overall Industry Employment Distributions for Females (Age 25-40)

2.1.2 Labor Demand Shifts

Between Industry The key fact is that the fraction of women working in skill-intensive industries grew over time, with the sharpest growth occurred during late 60s and early 70s. The period of late 60s and early 70s coincides with that of the legalization of the pill.

More generally, the data show a number of notable phenomena.

1. Women appeared to have a comparative advantage in skill-intensive (non-labor-intensive) industries.

   Figure 3 shows the overall industry employment distribution for female workers. In a given year, female workers disproportionately gravitated toward industries such as medicine, professions, education, manufacturing, and retail.

2. Between 1967 and 2001, a remarkable shift in female employment into skill-intensive industries occurred.

   In particular, women relocated and new entrants flocked to industries such as medicine, engineering, professions, and financial and business services. The overall increase in the employment share of these industries from the 1967-2001 period was about 71 to 78 percent. Meanwhile, the demand for female labor fell dramatically in industries such as low-tech and basic manufacturing and personal/entertainment services.

3. To sum up the above patterns for female employment, I group the industries into two broad categories, high and low-tech sectors, following the sector definition in section 4. I refer skill-intensive industries as the 'high-tech' sector and labor-intensive industries as the 'low-tech' sector. Basically, the industries in the upper two panels of figure 3 are 'low-tech' and those in the bottom two panels 'high-tech'.

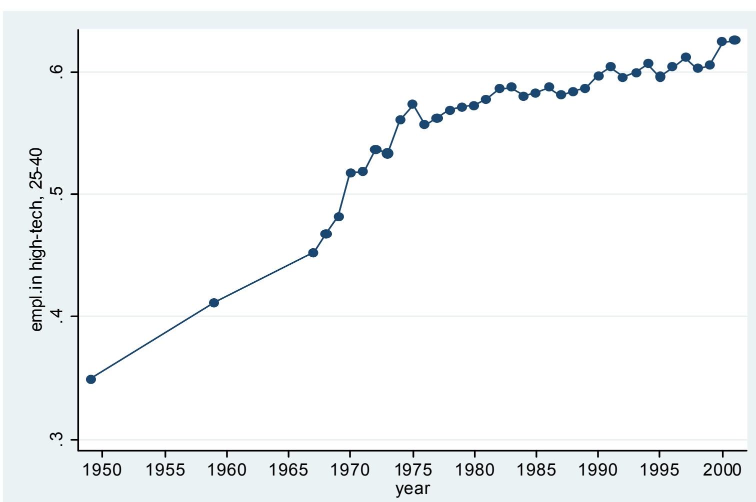

Figure 4. The Share of High-Tech Employment for Females

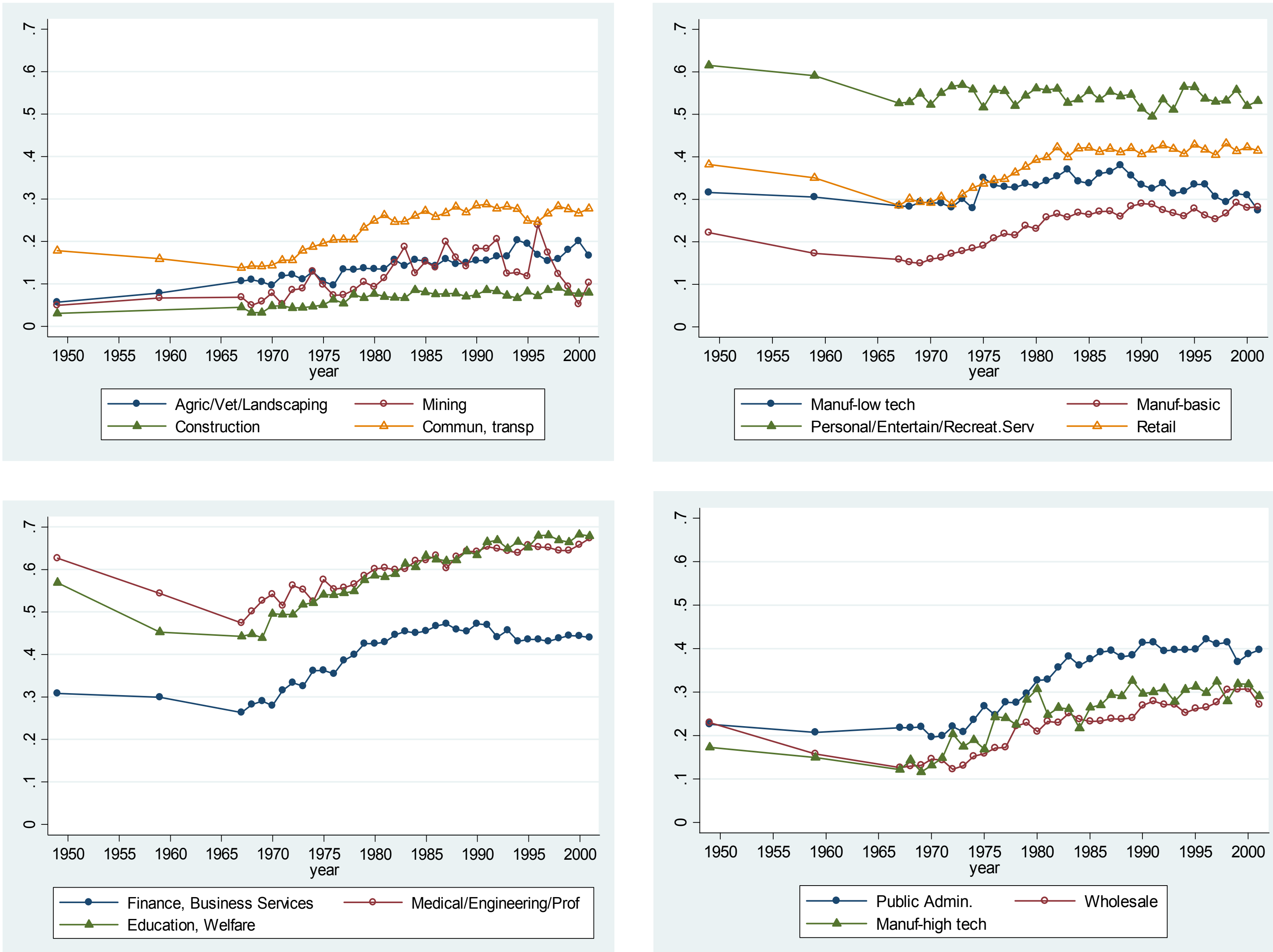

Figure 5. The Female Share of Employment by Industry (Age 25-40)

Figure 4 illustrates the share of employment in the high-tech sector. Two key facts emerge. First, the share of employment in the high-tech sector for women grew around twofold between 1949 and 2001. By 1970, over half of female workers worked in the high-tech sector. Second, the increase was sharpest during the 70s.

Within Industry The main fact is that women have become the dominant gender in the high-tech sector since the mid 80s.

1. Relative to men, women appeared to have a comparative advantage in skill-intensive (non-labor intensive) industries.

   Figure 5 indicates that in any given year women dominated in industries such as medicine, engineering, professions, education, welfare, and personal, entertainment and recreation services; they represented over half of the employment in these industries. Over time, females' share in these industries grew over 10 percent, except for the entertainment and recreation services.

2. When grouping the industries into two sectors, figure 6 shows that

   (a) Between 1959 and 2001, the female share in the high-tech sector grew about 77 percent. Women have become the dominant gender in the high-tech sector since the 80s.

   (b) The female share in the low-tech sector dropped sharply during the 60s, picked up in the 70s, and has been essentially flat since the 80s.

   (c) In any given year, women were predominately found in the high-tech than the low-tech sector.

   (d) As female labor participation grew over time, the trends on female share in both sectors indicate most women might have entered the high-tech sector.

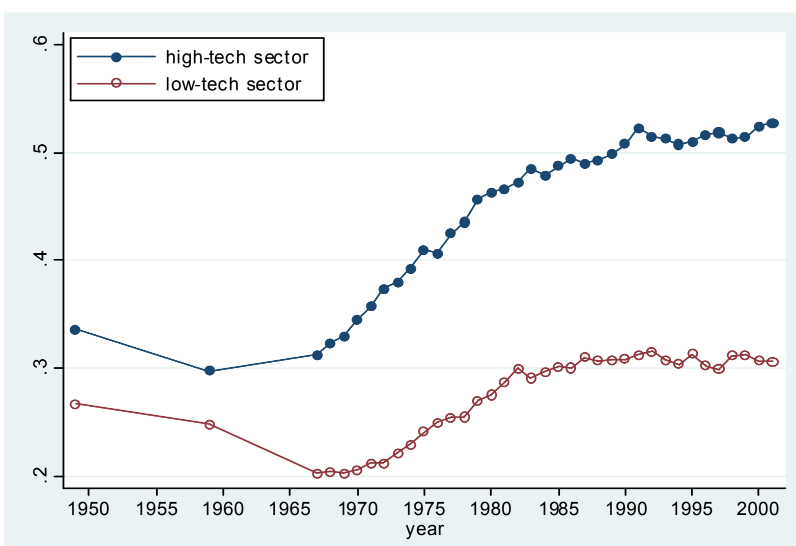

Figure 6. The Female Share of Employment, by sectors

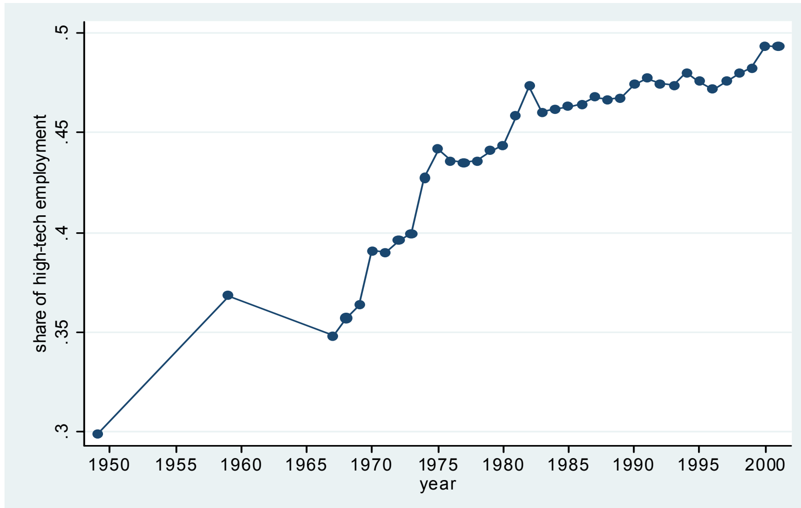

Figure 7. The Share of Employment in the High-Tech Sector

That the share of women rose in the low-tech sector during the 70s and early 80s does not necessarily imply more women joined the sector. Figure 7 shows that the share of total employment in the high-tech sector expanded about 34 percent during 70s and early 80s. This fact and the between-industry fact that shows a falling proportion of women in the low-tech sector (figure 2), imply that men left the low-tech sector at a faster rate than women.

2.2 Sex-Biased Technological Change

I define sex-biased technological change as technological change that has disproportionately affected women's productivity, helping women to utilize their cognitive ability more fully. It is prevalent in developed countries and most of the developing world in recent years.

The contraceptive pill is one example of sex-biased technological change. Technological progress in nutrition and food distribution in developing countries also disproportionately benefits women.[14] In a series of studies, Sen (1990a,b) illustrated that women in the developing world are more vulnerable to malnutrition and mortality than men, due to gender bias in the allocation of resources, health, and nutrition. Sen argued that gender bias in the allocation of resources causes abnormally high sex ratios and development problems.[15] He coined the phrase 'missing women' to refer to the number of women who died as a result of lack of access to health and nutrition in parts of the developing world. The estimated number of 'missing women' is larger than the total number of casualties of all famines in the 20th century. It also exceeds the death toll of both World Wars

[14] For example, there have been sizable improvements in Pakistan, Bangladesh, and most countries of the Middle East, North Africa, and Latin America.

[15] Examples from other studies include Rosensweig and Schulz (1982).

combined and the number of casualties of major epidemics such as the 1918-20 global influenza epidemic.

In the last three decades, life expectancy has increased 20 percent faster for women than for men. Where the high-tech sector is relatively less developed in these countries, lower rates of child mortality and higher rates of female labor force participation are typically observed in countries with higher levels of female education.

2.3 The Pill

The key facts from this section are: (1) the pill helped women acquired general skill, i.e. college education, and (2) current pill consumption was associated with a higher participation in the high-tech sector and a wage premium.

The data are drawn from the National Survey of Family Growth 1988 and 1995. All statistics are weighted. Detail sample description and selection can be found in the Data Appendix.

How are the labor market characteristics between pill-users and pill-free women compared? Table 1 shows the relation by four age groups.. The data show that there was no discernible difference between pill-users and pill-free women in school attendance, although slightly more pill users of age 20-24 attended school. This may imply the pill helped the acquisition of general education (college) since this age group makes up most of college graduates. For professional trainings such as doctors and lawyers mentioned in Goldin and Katz (2002), the age group 25-29 is more relevant. But pill-users and pill-free women appeared to have similar school attendance rate in this age group.

<insert table 1>

More striking differences are found in the labor market characteristics. The data show that 5-16 percent more pill-users worked in the high-tech sector, and the percentage was highest for the 25-29 group. Pill-users also appeared to earn a wage premium.

3 A Simple Model

I first describe the supply side, followed by the demand side, equilibrium definition, innovation, and a discussion. The discussion contains empirical predictions of the model on sector allocation and wages. Specifically, I show that sex-biased technological change expands the high-tech sector, with a larger proportion of women than men entering the sector. I also show that men are endogenously more productive than women in each sector, and that predictions on productivities hinge on the ability distribution being bivariate normal.

3.1 The Supply Side

The economy consists of two groups (g) of workers: men (m) and women (f). Each worker supplies one unit of labor inelastically. Each worker is bundled with two types of ability a, cognitive c and physical p ability: $a = \{c, p\} \in A \subset \Re^2_+$. Ability has a continuous and differentiable bivariate density function $h_g(c, p)$, $g = \{m, f\}$. Ability is measured in terms of efficiency units. It is assumed to be exogenously given so that investment in human capital is ignored.

Note that the assumption of exogenous human capital is restrictive and can be disputed both on empirical and theoretical grounds. I have basically three reasons for such an assumption. First, treating human capital as exogenous allows me to keep the analysis tractable. In the short run, it is plausible that the aggregate stock of skill is roughly fixed. Second, this assumption allows me to highlight the interesting mechanisms how changes in observed cognition affects women's economic progress. One could allow agents to choose the level of human capital such as in Rosen and Willis (1979), Acemoglu (1998), and Galor and Moav (2000). An alternative approach would be to consider human capital production given workers' ability endowment, or to extend Acemoglu's framework so that agents choose whether to go to school or work each period. While the analysis would become more complicated, the gain in economic insight would be minor. The third reason is that I want to think about sex-biased technological change to be more general than enhancing education, it can include on-the-job training or greater use of ability, any of these channels helps women bring their cognitive ability to the market.[16] As I shall show in the data section, our definition of skill is not equivalent to college graduates.

Women under-utilize their innate cognitive ability compared to men because of constraints from pregnancy. The simplest way to think about this is to consider women's innate cognitive ability to be reduced by a fixed amount, $\tau > 0$.

Assumption 1. The observed cognitive ability of women is $\overline{c}_f = c_f - \tau < \overline{c}_m = c_m$.

Note that Assumption 1 differs from viewing τ as discrimination on two grounds. First, if men and women differ by wages, say, because of discrimination, then discrimination will show up as a form of a lower skill price received by women in both sectors, not in terms of ability. In addition, improvements in the utilization of cognitive ability (a smaller τ) have differential effects on mean ability used in each sector (see section 3.5), but changes in discrimination affects the skill price received by women uniformly. Second, under-utilization of cognitive ability only applies to young women (child-bearing age) but discrimination against women affects all women. One interesting extension is to build a model to separately identify changes in discrimination and ability.

WLOG men are stronger in physical ability, $p_f < p_m$. Thus, men have an absolute advantage in both types of ability. Driven by the facts shown in section 2.1, I also have the following assumption.

Assumption 2. Women have a comparative advantage in using cognitive ability relative to men using physical ability on average.

Income maximizing workers choose sectors according to comparative advantage as in

[16] Some abilities such as building teams and communication do not require certificates and are nonetheless essential for management jobs.

Roy (1951). As in Roy's framework, relative ability responds elastically to skill premium. If instead, workers were bound to given task, the implications of our model will be the same, but innovation that affects skill premium would not generate reassignment of workers to jobs.

Define the relative efficiency of a worker with cognitive vs physical ability as $t_m = \frac{c_m}{p_m}$ and $t_f = \frac{\bar{c}_f}{p_f}$.A worker with relative efficiency t^*will be indifferent between performing jobs requiring physical and cognitive ability when the rewards for using each ability are equalized, i.e.

$$t^* = \frac{w_p}{w_c},$$

where w_a is the price per efficiency unit of labor using ability $a = \{c, p\}$. A worker supplies cognitive skill to labor service if $t_g >= t^*$ and supplies physical skill otherwise. The circles in figure 8 represent the bivariate density of cognitive and physical skills. Workers to the left of the ray of the skill-price ratio choose the high-tech sector. A higher relative skill-price rotates the ray downward, letting more workers choose the high-tech sector.

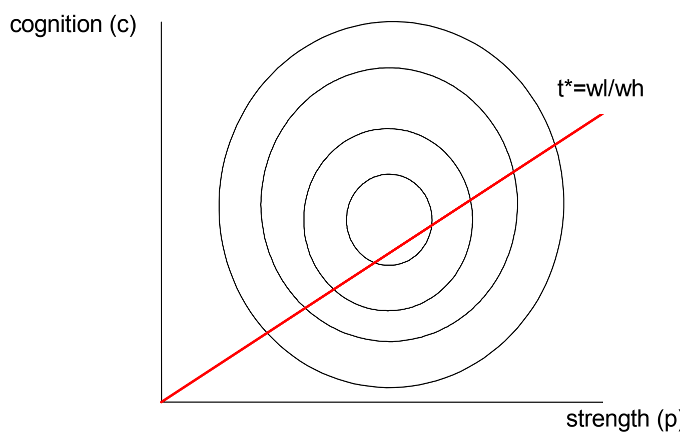

Figure 8. A Contour Plot of Ability Distribution

The following equivalence is standard. Let $H(x, y)$ denote a class of bivariate cumulative distribution functions identical up to a translation of location. For any particular x,

$$H(x, y) = G(x - \mu, y),$$

for any $\mu \in \Re^1$. I assume that H is strictly increasing. I consider H to be the distribution of innate ability and G the distribution of observed ability (for women). Thus, the observed distribution is a downward shift of the contours in figure 8, while the truncation point for cognitive ability pt^* remains unchanged. The proportion of women participating in the high-tech sector can be written as

$$K_f = \int\int_{pt^*} dG(c,p) = \int\int_{pt^*+\tau} dH(c,p). \quad (1)$$

Setting $\tau = 0$, the probability for men has a similar expression.

The relative labor supply for cognitive skill is the ratio of the total population supplying its cognitive skill N_c to that supplying physical skill N_p,

$$\frac{N_c}{N_p} = \frac{N_m K_m + N_f K_f}{N_m \overline{K_m} + N_f \overline{K_f}}, \quad (2)$$

where $\overline{K_g} = 1 - K_g$ and N_g represents the exogenous labor inputs of gender g, $g \in \{m, f\}$. By Assumption 2, a larger proportion of women are above t^*, i.e. $K_f > K_m$.

All consumers have linear preferences given by $\int_0^\infty Ce^{-rt}dt$, where C represents consumption and r is the rate of time preference, which will also be the interest rate. The time arguments are suppressed for simplification so long as this causes no confusion.

3.2 The Demand Side

The demand side is standard. Consumption, investment in machines I, and total R&D expenditure R come out of an output aggregate, $C + I + R <= Y \equiv [\gamma Y_L^\rho + (1-\gamma) Y_H^\rho]^{1/\rho}$. The production function, Y, indicates that the aggregate output is produced from two intermediate goods, Y_L (low-tech or labor-intensive goods) and Y_H (high-tech or cognitive-intensive goods), with elasticity of substitution $\varepsilon = 1/(1-\rho)$, where $-\infty < \rho \leq 1$, and γ is a distribution parameter which determines how important the two goods are in aggregate production.

This production function indicates that men and women are perfect substitutes in production. Is this assumption empirically plausible? Using the WWII mobilization as a natural experiment, Acemoglu et al. (2004) find that female and male labor inputs are highly, though not perfectly, substitutable. Even if men and women are perfect substitutes in production, cognitive and physical ability are imperfect substitutes. Workers choose sectors according to their comparative advantage. Thus, we see different employment distributions between men and women (section 2.1).

Intermediate goods The production function of the two immediate goods is

$$\begin{aligned} Y_L &= \frac{1}{1-\alpha}\left(\int_0^{N_L} x_L(j)^{1-\alpha} dj\right) \overline{N}_p^\alpha \\ Y_H &= \frac{1}{1-\alpha}\left(\int_0^{N_H} x_H(j)^{1-\alpha} dj\right) \overline{N}_c^\alpha \end{aligned} \quad (3)$$

where $\alpha \in (0,1)$, and $\overline{N}_p$ and $\overline{N}_c$ are the number of workers employed (demanded) with skill p (physical) and skill c (cognitive) in each sector. $x_L(j)$ denotes the amount of the $j-th$ $p-$complementary machine used in production. The range of machine that can be used with factor p is denoted by N_L. The production function for the other intermediate uses $c-$complementary machines and is explained similarly. Skill-biased technological progress will take the form of increases in N_L and N_H, i.e. technological change expands the range of machines that can be used with the respective workers' ability.

Product markets are competitive. Producers in the sector s intermediate good market take the prices of their goods p_s, wages w_H and w_L, the rental prices of all machines $\chi_s(j)$, and the range of machines N_s, as given, and solve the following maximization problem

$$\max_{N_a, \{x_s(j)\}} p_s Y_s - w_s \overline{N}_a - \int_0^{N_s} \chi_s(j) x_s(j) dj. \tag{4}$$

The first-order condition with respect to x_s gives the sectoral machine demand as

$$x_s(j) = \left[\frac{p_s}{\chi_s(j)}\right]^{1/\alpha} \overline{N}_a, \tag{5}$$

which shows a downward sloping demand schedule. Now, take the first-order condition with respect to N_a, and the equilibrium wage rate for workers with ability a in sector s is

$$w_a = \frac{\alpha}{1-\alpha} p_s \overline{N}_a^{\alpha-1} \left(\int_0^{N_s} x_s(j)^{1-\alpha} dj\right). \tag{6}$$

Technology monopolist Machines in both sectors are supplied by technology monopolists, whose innovation decisions determine N_L and N_H. Note that the set of machines used in the production of the two intermediate goods are different, allowing technical change to be biased. Each monopolist sets a rental price $\chi_L(j)$ or $\chi_H(j)$ for the machine it supplies to the market. Suppose all machines depreciate fully after use and the marginal cost of production is the same for all machines and equal to ψ in terms of the final good. Suppose for now that N_L and N_H are given.

The profits of a monopolist is $\pi_s(j) = [\chi_s(j) - \psi] x_s(j)$. Since the demand curve for machines facing the monopolist (5) is isoelastic, the profit-maximizing price will be a constant markup over marginal cost: $\chi_s(j) = \psi/(1-\alpha)$. To simplify expositions, normalize ψ to be $(1-\alpha)$ so that all machine prices are given by

$$\chi_L(j) = \chi_H(j) = 1.$$

Using the machine demands from (5) and the normalized prices, profits of technology monopolists become

$$\pi_L(j) = \alpha p_L^{1/\alpha} \overline{N}_p \text{ and } \pi_H(j) = \alpha p_H^{1/\alpha} \overline{N}_c. \tag{7}$$

3.3 Equilibrium

Definition: An equilibrium requires (i) a set of prices for machines, $\chi_L(j)$ or $\chi_H(j)$, that maximize the profits of technology monopolists, (ii) machine demands from the two intermediate good sectors, $x_L(j)$ or $x_H(j)$, that maximize intermediate good producers' profits, (iii) the level of factor supply, N_p and N_c, that maximizes workers' income and clears the labor market, i.e. $N_p = \overline{N}_p$ and $N_c = \overline{N}_c$, and (iv) factor and product prices, w_H, w_L, p_H, and p_L that clear the respective markets. The range of machines N_L and N_H that clears the technology market will be determined in the next section.

Let me characterize the equilibrium taking the state of technologies N_L and N_H as given. Complementarity between technology and ability induces the high-tech sector to employ only cognitively-skilled workers and the low-tech sector to employ only physically-skilled workers. In equilibrium, the sectoral-skill price must equate the associated industry wage rate,

$$w_c = w_H \;\text{ and }\; w_p = w_L. \tag{8}$$

Thus, the equilibrium threshold level of relative productive ability equals the inverse relative skill reward, $t^* = w_L/w_H$. From (1), it is clear that the probability of high-tech sector participation is positively related to the relative skill reward, giving rise to an upward sloping relative skill supply curve.

To solve for relative skill reward, let me first solve for the relative price ratio. The number of firms in each intermediate good sector and the price of the final good are normalized to 1. The product markets for the two intermediate goods are competitive; market clearing implies that their relative price, p, satisfies $p = \frac{p_H}{p_L} = \frac{1-\gamma}{\gamma}\left(\frac{Y_H}{Y_L}\right)^{\rho-1}$. Substituting (5) into the production functions in (3),

$$p = \left(\frac{1-\gamma}{\gamma}\right)^{\alpha/(1-\rho)\sigma}\left(\frac{N_H N_c}{N_L N_p}\right)^{-\alpha/\sigma}, \tag{9}$$

where σ is the elasticity of substitution between the two factors, N_c and N_p, defined as $\sigma \equiv \frac{1-\rho(1-\alpha)}{1-\rho}$. Using (5), (6), (8), and then substituting for (9),

$$\frac{w_H}{w_L} = p^{1/\alpha}\frac{N_H}{N_L} = \left(\frac{1-\gamma}{\gamma}\right)^{1/(1-\rho)\sigma}\left(\frac{N_H}{N_L}\right)^{(\sigma-1)/\sigma}\left(\frac{N_c}{N_p}\right)^{-1/\sigma}. \tag{10}$$

Relative skill reward is decreasing in relative skill supply. This is the usual substitution effect. With sector choice, the relative ability supply $\frac{N_c}{N_p}$ in (2) and the relative skill reward $\frac{w_H}{w_L}$ in (10) are jointly determined in equilibrium.

3.4 Innovations

Suppose now the state of technology is endogenously determined. It is a knowledge-based R&D specification of Rivera-Batiz and Romer (1991) where spillover from past research to current productivity is necessary to enable factors to become more productive over time and thereby sustain growth. In other words, the degree of state dependence in R&D, which relates to how future relative costs of innovation are affected by the current composition of R&D, will have an important effect on the direction of technical change.

The production function for new machine varieties can depend on the state of knowledge in both sectors, a specification considered in Acemoglu (2001):

$$\dot{N_H} = \eta_H N_H^{(1+d)/2} N_L^{(1-d)/2} R_H \text{ and} \dot{N_L} = \eta_L N_H^{(1-d)/2} N_L^{(1+d)/2} R_L, \tag{11}$$

where η_s is a parameter allowing the costs of innovation in each sector to differ, R_s is the constant supply of researchers in sector s, and d ($d <= 1$) measures the degree of state-dependence. Equation (11) says that one unit of final good spent for hiring high-tech researchers will generate $\eta_H N_H^{(1+d)/2} N_L^{(1-d)/2}$ new varieties of high-tech machines. A researcher who innovates a new machine variety receives a perfectly enforced patent on this machine.

When $d = 0$, there is no state-dependence and $\left(\partial \dot{N_H}/\partial R_H\right) / \left(\partial \dot{N_L}/\partial R_L\right) = \eta_H/\eta_L$ irrespective of the levels of N_H and N_L. When $d = 1$, state-dependence is at maximum and $\left(\partial \dot{N_H}/\partial R_H\right) / \left(\partial \dot{N_L}/\partial R_L\right) = \eta_H N_H/\eta_L N_L$, so an increase in the stock of low-tech machines today makes future low-tech innovations cheaper and has no effect on the cost of high-tech innovations.

The net present discounted value of profits can then be written as

$$rV_L - \dot{V_L} = \pi_L \text{ and } rV_H - \dot{V_H} = \pi_H. \tag{12}$$

On the balanced growth path, prices p_L and p_H are constant, and N_L and N_H grow at the same rate. This implies that $\dot{V}$ in (12) becomes zero, and V_H/V_L is constant. Technology monopolists have incentive in innovating for both sectors if this ratio, or the relative profits π_H/π_L, is exhausted by the inverse ratio of $\left(\partial \dot{N_H}/\partial R_H\right) / \left(\partial \dot{N_L}/\partial R_L\right)$. The technology market clearing condition thus captures the relative costs of R&D being dependent on the current state of technology:

$$\eta_H N_H^d \ \pi_H = \eta_L N_L^d \pi_L. \tag{13}$$

This condition says that it is equally profitable to invest in inventing either high-tech or low-tech machines, allowing both N_L and N_H to grow along the balanced growth path.

Using (7) and (9), and the technology market clearing condition (13) , we can solve the equilibrium relative technology as

$$\frac{N_H}{N_L} = \left(\frac{\eta_H}{\eta_L}\right)^{\frac{\sigma}{1-d\sigma}} \left(\frac{1-\gamma}{\gamma}\right)^{\frac{1}{(1-d\sigma)(1-\rho)}} \left(\frac{N_c}{N_p}\right)^{\frac{\sigma-1}{(1-d\sigma)}}, \tag{14}$$

where $1/(1-\rho)$ is the elasticity of substitution between the two intermediates and $\sigma = (1-\rho(1-\alpha))/(1-\rho)$ is the elasticity of substitution between the two factors. As technology is endogenized, equation (14) shows that the relation between the relative bias of technology $\frac{N_H}{N_L}$ and the relative ability supply $\frac{N_c}{N_p}$ is determined by the elasticity of substitution between the two factors and the degree of state-dependence. Substituting (14) into (10), we obtain

$$\frac{w_H}{w_L} = \left(\frac{\eta_H}{\eta_L}\right)^{\frac{\sigma-1}{1-d\sigma}} \left(\frac{1-\gamma}{\gamma}\right)^{\frac{(1-d)}{(1-d\sigma)(1-\rho)}} \left(\frac{N_c}{N_p}\right)^{\frac{\sigma-2+d}{(1-d\sigma)}}. \tag{15}$$

I focus on the balance growth path. The condition $1 > d\sigma$ must be satisfied so that transitory dynamics will take us back to stability. In the case of an extreme state-dependence, this stability condition requires two factors to be gross complements, i.e. $\sigma < 1$. Equation (15) also shows that an increase in the relative abundance of a factor raises its relative marginal product when $\sigma > 2 - d$. When $d < 1$, the two conditions $1 > d\sigma$ and $\sigma > 2 - d$ are satisfied simultaneously.

When the two factors are gross substitutes, $\sigma > 1$, an increase in the relative factor supply $\frac{N_c}{N_p}$ leads to skill-biased technological change because skill-complementarity technologies have a greater market and it is more profitable to innovate for larger clienteles. A higher level of $\frac{N_c}{N_p}$ corresponds to skill-biased technological change, and technology will be endogenously biased in favor of the more abundant ability.

It is important to note that in (15) the relative factor supply is more elastic than that in (10) because machines are now adjusted to the relative factor supply (workers). When technological change is endogenous, an increase in $\frac{N_c}{N_p}$ changes the direction of technological progress and leads to more R&D in the high-tech sector. With a sufficiently large technical effect, $\sigma > 2 - d$, an increase in the relative abundance of a factor raises its relative marginal product. This is the case for 'strong induced-bias' technology (Acemoglu (2001)). The long-run skill premium is upward sloping.

3.5 Discussion

In this section, I overview the model characteristics and then show the key predictions of the model on sector allocation and wages. I show that men are endogenously more productive than women in each sector, and that predictions on wages hinge on the ability distribution being bivariate normal.

3.5.1 Overview

By construction, the model is one with a two-tier sorting system. Sex-biased technological change is the catalyze for a cascade of impacts on workers' reallocation. First, sex-biased technological change raises women's productivity, leading more women to sort themselves to the high-tech sector. One might be tempted to argue that the result that sex-biased technological change triggers reallocation of labor from low to high-tech sector is not surprising, and that all I have done is to show that such technological change shifts the relative skill supply curve to the right. But the mechanism at work in our model is richer.

The expansion of the high-tech sector directs firms to innovate towards technologies in that sector, as it becomes more profitable to innovate towards technologies in the high-tech sector. This creates the second tier sorting. A sufficiently powerful composition effect lifts the skill premium. Insofar as relative factor supply responds elastically to skill premium, a higher skill premium encourages more workers to enter the high-tech sector.

If dynamics are introduced in the model, the expansion of the high-tech sector in turn promotes a higher skill premium. This encourages more participation in the high-tech sector, which encourages skill premium, and so on. Hence, rather than a rightward shift in the relative factor supply curve, what is at work with the dynamics is a feedback effect stemming from general equilibrium effects, creating a vicious cycle of expanding markets for skilled and rising skill premium.

3.5.2 Sector Allocation

Sex-biased technological change corresponds to a fall in τ so that it raises $\overline{c}_f$, directly leading more women to choose the high-tech sector. Taking the derivative of the probability of women participating in the high-tech sector, K_f in (1), with respect to τ,

$$\frac{\partial K_f(\tau)}{\partial \tau} = -\int h_f(p_f t^* + \tau, p)dp - \frac{\partial t^*(\tau)}{\partial \tau}\int h_f(p_f t^* + \tau, p)p_f dp.$$

The first term on the right-side of the equation is the direct effect of τ.Graphically, sex-biased technological change shifts the contour of the bivariate density up. The new density is represented by the blue contours (figure 9). So, a fall in τ directly raises the share of women in the high-tech sector.

The second term on the right-side of the equation is the feedback effect from changes in relative skill reward. A positive feedback reduces t^*, the inverse skill premium; so $\frac{\partial t^*(\tau)}{\partial \tau} > 0$. This encourages even more workers (both men and women) to participate in the high-tech sector (figure 10). More male workers participate in the high-tech sector because the feedback effect benefits all workers. Consequently, the high-tech sector expands. If the feedback is negative, more women enter the high-tech sector provided that the direct effect dominates the indirect effect.

Proposition 1 *Sex-biased technological change expands the high-tech sector if the feedback is positive or if the feedback is negative and the direct effect dominates.*

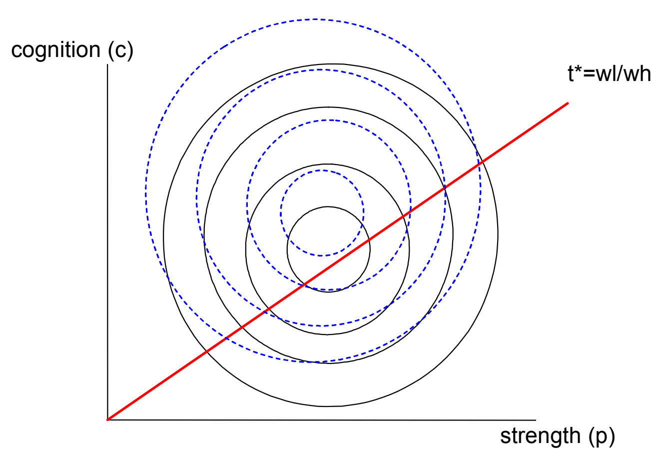

Figure 9. Sex-Biased Technological Change Shifts the Relative Share of Ability

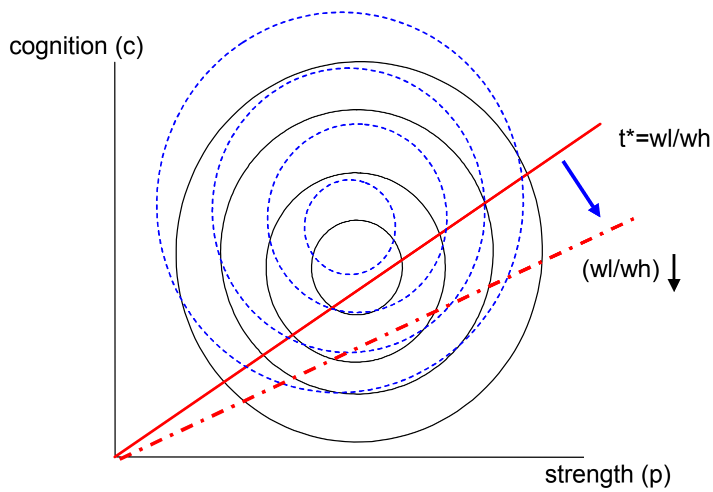

Figure 10. A Positive Feedback

Sex-biased technological change not only implies between-industry allocations from low to high-tech sector, but it also implies an increase in the female employment share in the high-tech sector, which is $\frac{N_f K_f}{N_m K_m + N_f K_f}$. These within and between-industry employment share predictions are consistent with the relative labor demand facts shown in figures 2 and 4 in section 2.

3.5.3 Wages

Individual workers' wages in the high and low-tech sectors, respectively, are

$$\begin{array}{llll} w_H \overline{c}_g & \text{if } \overline{c}_g & > & = p_g t^* \\ w_L p_g & \text{if } \overline{c}_g & < & p_g t^* \end{array},$$

where $g = \{m, f\}$. Inter-sector wage inequality (or within sex inequality) arises because of differences in sector wages and productivity. In what follows, I assess gender wage difference in each sector separately, starting with the high-tech sector.

Proposition 2 *Men are more productive than women in the high-tech sector.*

Men and women are assumed to have the same innate cognition, yet men have higher productivity in the high-tech sector. Why? Part of it is due to their absolute advantage in 'observed' cognitive ability because they bear no cost of motherhood, i.e. $\tau = 0$ for men. The other part of it is due to selection. It occurs because women have a comparative advantage in cognition relative to men, fewer but brainier men self-select into the high-tech sector.

To see the selection effect, consider first the case $\tau = 0$. I shall show that even men and women have the same observed cognition, men are still more productive. This is similar to Galor and Weil's (1996) setting. The differences are those of heterogeneous workers and sector choice. Let $c_m = \overline{c}_f = c$. Then men's absolute advantage in strength implies women's comparative advantage in cognition compared to men. Suppose η represents the strength differential so that men and women's distributions are identical up to a translation of location, for any $\eta \in R^1$. For any particular y,

$$H_m(x, y) = H_f(x, y - \eta).$$

Let $\int V(pt^*, -\eta t^*)dp$ denote the truncated mean function, i.e. the expected value of cognition with cumulative distribution function H_f, conditional on c being greater or equal to pt^*. It can be expressed as

$$\begin{aligned}
E(c|c &> = pt^*) = \int V(pt^*, -\eta t^*)dp \\
&= \frac{\int \int_{pt^*} ch_f(c,p)dcdp}{\int \int_{pt^*} h_f(c,p)dcdp} \\
&= \frac{\int \int_{(p+\eta)t^*} (c - \eta t^*)\, h_m(c,p)dcdp}{\int \int_{(p+\eta)t^*} h_m(c,p)dcdp} \\
&= -\eta t^* + \int V((p+\eta)t^*, 0)dp
\end{aligned}$$

Let $\varphi = \int \int_{(p+\eta)t^*} h_m(c,p)dcdp$. Differentiating $E(c|c >= pt^*)$ with respect to η gives

$$\begin{aligned}
&\frac{\partial E(c|c >= pt^*)}{\partial \eta} \\
&= -t^* + \int V_1((p+\eta)t^*, 0)dp \\
&= t^* \left\{ -1 + \frac{1}{\varphi} \left[-\int (p+\eta)t^* h_m((p+\eta)t^*, p)dp + \int V((p+\eta)t^*, 0) h_m((p+\eta)t^*, p)dp \right] \right\} \\
&= t^* \left\{ -1 + \frac{1}{\varphi} \int \left[V((p+\eta)t^*, 0) - (p+\eta)t^* \right] h_m((p+\eta)t^*, p)dp \right\}.
\end{aligned}$$

Because H is strictly increasing, $V((p+\eta)t^*, 0) > (p+\eta)t^*$, and $\int V_1((p+\eta)t^*, 0)dp > 0$. Therefore, a small shift to the right in the location of the bivariate density function (a fall in η) will increase the conditional expectation if and only if $\int V_1((p+\eta)t^*, 0)dp < 1$. In general, given a particular H, I can check whether this condition is satisfied. A number of studies have shown affirmative results with log-concave distributions in a univariate dimension, but no confirmation exists for bivariate distributions.[17] Numerical experiments

[17] For univariate studies, see, for example, Goldberger (1980).

using a bivariate normal distribution indicate the slope of its truncated mean function is less than one everywhere.

Assumption 3. $H(.,.)$ has a bivariate normal distribution.

I shall apply *Assumption 3* to the rest of the discussion.

Lemma 1. $\int V_1((p+\eta)t^*,0)dp < 1$.

Lemma 1 indicates a fall in the strength differential raises women's conditional mean cognition, i.e. $\frac{\partial E(c|c>=pt^*)}{\partial \eta} < 0$. So when women become physically stronger, more of them choose the low-tech sector. Those in the high-tech sector have higher cognitive prowess. Analogously, a larger proportion of men than women choose the low-tech sector because they are physically stronger. This induces fewer but brainier men to choose the high-tech sector.

Corollary 1. Men are more productive than women in the high-tech sector even men and women have the same observed cognition.

In the case of $\tau > 0$, both absolute advantage in men's observed cognition and the selection effect contribute to men's higher productivity. The ability distribution of men first-order stochastically dominates that of women. The truncated mean cognition for women, which is also denoted by $\int V((p+\eta)t^*,-\tau)dp$, is:

$$\begin{aligned} E(c|c &> = p_f t^*) \\ &= \int V((p+\eta)t^*,-\tau)dp \\ &= \frac{\int\int_{(p+\eta)t^*+\tau}(c-\eta t^*-\tau)\,h_m(c,p)dcdp}{\int\int_{(p+\eta)t^*+\tau} h_m(c,p)dcdp} \\ &= -\eta t^* - \tau + \frac{\int\int_{(p+\eta)t^*+\tau} ch_m(c,p)dcdp}{\int\int_{(p+\eta)t^*+\tau} h_m(c,p)dcdp} \\ &= -\eta t^* - \tau + \int V((p+\eta)t^*+\tau,0)dp. \end{aligned}$$

Let $\varsigma = \int\int_{(p+\eta)t^*+\tau} h_m(c,p)dcdp$. Differentiating $E(c|c>=p_f t^*)$ with respect to τ and rearranging, we have

$$\begin{aligned} & \frac{\partial E(c|c>=p_f t^*)}{\partial \tau} \\ = \quad & -1+\frac{1}{\varsigma}\int\left[V((p+\eta)t^*+\tau,0)-(p+\eta)t^*-\tau\right]h_m((p+\eta)t^*+\tau,p)dp. \end{aligned}$$

As shown in the case of $\tau=0$, $V((p+\eta)t^*+\tau,0)>(p+\eta)t^*+\tau$ because H is strictly increasing; so the second term on the right-side of the second equality, or $\int V_1((p+\eta)t^*+\tau,0)dp$, is positive. By *Assumption 3,* the slope of the truncated mean is less than 1: $\int V_1((p+\eta)t^*+\tau,0)dp<1$. Therefore, an upward shift in the location of the bivariate density function (a fall in τ) will increase the conditional expectation of cognition. This is the direct effect of sex-biased technological change.

An indirect effect is also present. It occurs because τ affects (the inverse) skill premium. Again, two cases occur. First, when the higher relative share of skill gives rise to a powerful market-size effect, skill premium increases, i.e. $\frac{\partial t^*(\tau)}{\partial \tau}>0$. From the derivation above, we can see that differentiating $E(c|c>=p_f t^*)$ with respect to $t^*(\tau)$ gives $\int V_1((p+\eta)t^*+\tau,0)(p+\eta)dp>0$. Together, the indirect effect of τ is given by

$$\frac{\partial E(c|c>=p_f t^*)}{\partial t^*(\tau)}\frac{\partial t^*(\tau)}{\partial \tau},$$

which is positive. The indirect effect that raises the volume of women in the high-tech sector, which is made up of those with less cognition than women who are already in the high-tech sector. This creates a trade-off with gains in productivity from the direct effect. Second, if the feedback effect is negative, i.e. $\frac{\partial t^*(\tau)}{\partial \tau}<0$, the indirect effect becomes negative, same as the direct effect. So, an upward shift in the location of the bivariate density function (a fall in τ) will increase the conditional expectation of cognition.

Corollary 2. $\frac{\partial E(c|c>=p_f t^*)}{\partial \tau}<0$ *if the feedback is negative or if the feedback is positive and the direct effect dominates.*

What about the conditional mean productivity for men? Sex-biased technological change has only an indirect effect on men via the feedback effect from skill premium. If the feedback is positive, the increase in the share of men in the high-tech sector reduces their conditional mean productivity. Alternatively, if the feedback is negative, the conditional mean productivity increases.

Let me now turn to the low-tech sector.[18] In the low-tech sector, men are also more productive than women because they have an absolute advantage in strength, even more of them participate in the sector. To see the effect of sex-biased technological change, let me examine the truncated mean strength for women:

[18] Derviations in the low-tech sector are similar to those in the high-tech sector and are therefore not shown.

$$E(p_f|c_f < p_f t^*) = \frac{\int\int^{(p+\eta)t^*+\tau} p h_m(c,p)dcdp}{\int\int^{(p+\eta)t^*+\tau} h_m(c,p)dcdp}.$$

Differentiation with respect to τ gives a negative sign for both the direct and the indirect effect. Intuitively, sex-biased technological change directly reduces the amount of workers in the low-tech sector, those who remain are relatively strong.

Proposition 3 *In the low-tech sector, sex-biased technological change raises the productivity of women more than that of men.*

This proposition indicates that women in the low-tech sector are catching up with men's productivity, which is consistent with empirical evidence in Fortin and Lemieux (2000). Fortin and Lemieux compared male and female wage distributions between 1979 and 1991, and find that women at the lower wage distribution are catching up with men.

The average wage for gender g is

$$\overline{w}_g = w_H E(c_g|c_g >= p_g t^*)K_g + w_L E(p_g|c_g < p_g t^*)\overline{K}_g. \tag{16}$$

With sex-biased technological change, men and women become more similar in cognition . As long as this productivity effect dominates the volume effect, the gender premium increases.

4 Data

I use three datasets in my analyses: the March Current Population Survey, National Longitudinal Survey of Youth and its Geocode data, and the Patent data from the NBER. The main data source is the March CPS. When considered together, these datasets allow my study period to span from 1982 to 1996. The period of my analysis precludes a study on the exogenous variation in pill supply as in Goldin and Katz (2002). I describe all datasets and sample selection issues in detail in the Data Appendix.

In this section, I describe the method to categorize high and low-tech sectors among industries.

4.1 Technology Sector Definition

Based on the assumption of complementary between technology and skill, I use workers' skills to determine different technology sectors. Skill by itself is difficult to measure. I draw on data from the 1971 DOT, which was linked to the 1971 CPS. Our selection consists of non-farm workers whose ages were between 18 and 65.

I divide one-digit industries into two sectors: the low-tech sector (labor-intensive) and the high-tech sector (skill-intensive). Following the exposition from the analytical model, the low-tech sector corresponds to sectors that utilize workers' physical ability. I first sift out industries that mainly utilize workers' physical strength. The variable 'strength' takes five categories: sedentary, light, medium, heavy, and very heavy. I form a strength-dummy of value equals one if 'strength' equals heavy or very heavy. If the average value for the dummy variable in an industry exceeds the overall mean value, the industry is considered to belong to the low-tech sector. But the remaining may not necessarily be high-tech because some industries do not require strength or cognitive skill, for example the retail industry and personal services. To fine-tune for the high-tech sector, I use education levels as a measure for cognitive skill.[19] I obtain the mean education level for every one-digit industry. Not surprisingly, retail and personal service industries have mean education that is below the overall mean, so I group them as the low-tech sector. The division of the high and low-tech sectors is:

- High-tech sector: medicine/engineering/professional, education/welfare, finance/ business services, public administration, high-tech manufacturing, and wholesale trade.

- Low-tech sector: agriculture, mining, construction, low-tech manufacturing, basic manufacturing, communication/transportation, retail, and personal/ entertainment/ recreational services.

Definitions

- Skill premium: the mean wage in the high-tech sector divided by the mean wage in the low-tech sector.

- Relative skill supply: the number of workers in the high-tech sector divided by the number of workers in the low-tech sector.

The definitions of skill premium and relative skill supply differ from conventional definitions that rely on educational factors such as the college premium and stock of college to high-school graduates. In a sense, the definition here is more general because we do not impose education to measure skill perfectly. In fact, over and under-education, as well as variations in education, are noticeable in industry and occupation categories (e.g. Acemoglu (1999) and Pryor and Schaffer (1997)). Nonetheless, figure 11 shows that the trend in skill premium resembles that which can be found when 'college' is used as a measure for skill.

[19] The advantage of using education level is that it has a natural scale.

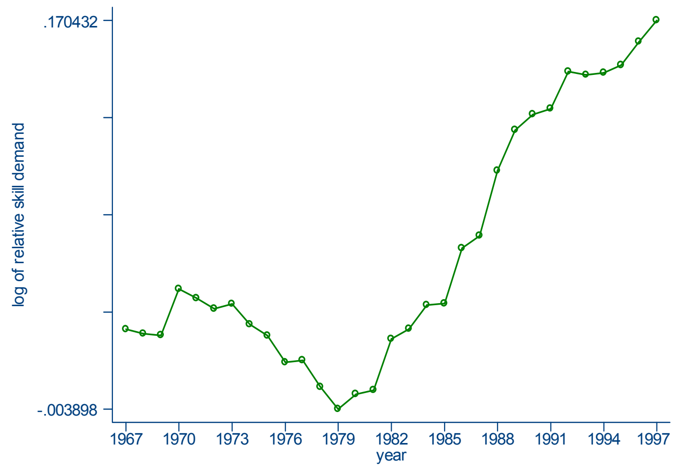

Figure 11. Skill Premium in terms of Technology Sectors, CPS (1968-1999)

5 Results

In this section, I first report the cross-year and cross-state correlations between relative skill supply and skill premium in section 5.1, followed by the 2SLS estimates in section 5.2. Section 5.3 describes the sector-allocation-adjusted 2SLS estimates. Section 5.4 presents results on wages.

5.1 Relative Skill Supply and Skill Premium

Before turning to our 2SLS analysis, I document the cross-year and cross-state correlations between relative skill supply and skill premium over 1976-1996 and 1982-1996. Most studies on wage structure cover the mid 70s. I compare the two different period to check whether a change in the time period affects the estimates qualitatively.

I start with time series regressions. Table 1 presents OLS regressions of log skill premium on log relative skill supply for the period 1976-1996. I report Huber-White robust standard errors. I start the estimation using standard ingredients in the demand equation similar as Katz and Murphy (1992):

$$\ln(y_t) = \alpha + \beta_1 \ln(c_t) + \beta_2 t + \varepsilon_t,$$

where y_t represents college premium, c_t represents relative skill (college) supply, t is a linear time trend, and ε_t is an unobserved disturbance.[20] Equation (19) of Katz and Murphy (1992, p.69) shows that $\beta_1 = -0.709$, which is equivalent to $\sigma = 1.41$ assuming an exogenous technological change framework. Column 1 of table 2 shows results using

[20] The model of Katz and Murphy (1992) offers limited interpretations because the assumption of exogenous technological change provides little empirical guidance, and so fitting a linear time trend alone is the most natural step to approach the problem. As the authors showed on p.71 of their article, the fit of their model was undesirable.

the above specification. The negative effect (though insignificant) of relative skill supply appears to be consistent with Katz and Murphy's finding.

However, the endogenous technological change model in this paper suggests a richer formulation: skill premium can be explained by the relative new machine varieties and the relative importance of each sector. Take the logarithm of equation (15) to obtain

$$\ln(\frac{w_H}{w_L}) = \frac{\sigma-1}{1-d\sigma}\ln\left(\frac{\eta_H}{\eta_L}\right) + \frac{(1-d)}{(1-d\sigma)(1-\rho)}\ln\left(\frac{1-\gamma}{\gamma}\right) + \frac{\sigma-2+d}{(1-d\sigma)}\ln\left(\frac{N_c}{N_p}\right). \quad (17)$$

The unit of observation is calender year t and state k, omitted in the equation. Note that there are three fundamental parameters from the model construction: d, σ which depends on ρ and α. My goal is to estimate $\frac{\sigma-2+d}{(1-d\sigma)}$ rather than separately identify each parameters.

What are the empirical contents of $\frac{\eta_H}{\eta_L}$ and $\frac{1-\gamma}{\gamma}$? I approximate relative new machine varieties using patent data, i.e. I use the ratio of the average number of a given patent measure in high to low-tech sectors as a proxy. I call this variable 'patent'. For example, I obtain the average number of citations received in high-tech sectors and divide it by the average number of citations received in low-tech sectors. As described in section 4, I use four measures of 'quality-adjusted' patent data. Patent innovation varies dramatically across the U.S. states, and so $\frac{\eta_H}{\eta_L}$ is state-specific.

Next, recall $(1-\gamma)$ and γ respectively represents the importance of high-tech and low-tech goods in aggregate production. Because γ is a distribution parameter, it can be estimated as a binary response model. I consider a logit model. Define $Y=1$ if the high-tech sector is important, and equal to 0 otherwise. The probability that $Y=1$ can be explained by a set of covariates ($\mathbf{X}$) can be written as $\Pr(Y=1) = F(\mathbf{X},\boldsymbol{\beta}) = \exp(\boldsymbol{\beta'}\mathbf{X})/(\mathbf{1}+\exp(\boldsymbol{\beta'}\mathbf{X}))$.The last equality is obtained assuming that $F(.)$ takes a logistic distribution. In this way, $\boldsymbol{\beta'}\mathbf{X} = \ln\left(\frac{1-\gamma}{\gamma}\right)$. The covariates in $\mathbf{X}$ include the logarithm of the energy price index, the logarithm of the general-purpose machinery price index, linear time trends, and a constant. So $\mathbf{X}$ only varies with time.

Define $\mathbf{X}_{1kt} = (\mathbf{X}_t,\text{patent}_{kt})$. Equation (17) can therefore be recast as

$$\ln(w_{kt}) = \beta_0 + \boldsymbol{\beta}_1'\mathbf{X}_{1kt} + \beta_2\ln(n_{kt}) + \varepsilon_{kt}, \quad (18)$$

where $w = \frac{w_H}{w_L}$, $n = \frac{N_c}{N_p}$, $\beta_2 = \frac{(\sigma-2+d)}{(1-d\sigma)}$ is the parameter of interest, and ε_{kt} is an unobserved disturbance.

Column 2 of table 2 shows the result from a regression of log skill premium on the logarithm of the energy price index, the logarithm of the general-purpose machinery price index, two linear time trends, log relative skill supply, and a constant. I follow the existing literature choosing linear time trends over time dummies. The first linear time trend, Time1, corresponds to the linear time trend from 1976 to 1981, and Time2 corresponds the trend from 1982 to 1997. Columns 3-6 shows results including a measure of the log of relative patent innovation. These results indicate a negative relationship between relative skill supply and skill premium. The elasticity of substitution between high and low-skill workers is around 1.66. This is consistent with findings in the existing literature on college premium which obtain elasticity of substitution between college and high-school students to be around 1.4-1.6. The patent variables are oddly negatively related to skill premium. I next consider the second time period 1982-1996 (table 3). The supply and the patent variables switch to positive signs. This indicates the time series results to be sensitive to changes in time period. Because results are robust to all patent definitions, in what follows, I show results using only 'generality' as my patent measure.

I next examine state-level data. All the regressions control for state dummies and are weighted by mean state population. Columns 1 and 2 of table 4 show that once controlled for state heterogeneity, both relative skill supply and relative innovation become positively related to skill premium.

Is the positive supply-demand relation that is driven by a sufficiently high elasticity of substitution between high and low-skilled workers real or illusory? The conclusions obtained in this section would be premature because variation in supply reflects both demand and supply forces. To the extent that relative skill supply responds elastically to skill premium, the OLS estimate of the effect of relative skill supply will be biased upward by simultaneity. This is because relative skill supply will be positively correlated with relative skill demand. In the next section, I estimate skill premium by 2SLS, using a set of exclusion variables that are potentially uncorrelated with skill premium.

5.2 The Impact of Relative Skill Supply on Skill Premium

To control for the endogeneity of the relative share of workers in the high-tech sector, I use instrumental variables based on the initial age composition of gender differences in employment (annual hours-worked), $\mathbf{M}_{kt}$. It is plausible that this factor affects the allocation of workforce but are exogenous to the change in relative skill reward within each state and year. I take these instruments to predict what the employment of males and females would be in each state given the current demographics on the basis of the time-invariant variable. In this model I also control for the share of the sample population with college and above (college+), some college, and high-school degrees in each state and year; I also control for the share of nonwhites and the share of pill users in each state and year. Let us refer this set of share variables as $\mathbf{X}_{2kt}$. The regression equation is

$$\ln(n_{kt}) = \alpha_0 + \boldsymbol{\alpha}_1'\mathbf{X}_{1kt} + \boldsymbol{\alpha}_2'\mathbf{X}_{2kt} + \boldsymbol{\alpha}_3'\mathbf{M}_{kt} + \alpha_k + u_{kt}, \tag{19}$$

where $\mathbf{X}_{1kt}$ represents a set of elements from the demand side including a linear time trend, and u_{kt} is an unobserved disturbance.

In column 3 of table 4 I report results from the 2SLS estimation (hereafter we refer these results as the baseline results). The results of these models show a negative (though insignificant) relation between skill premium and the relative share of skill, as expected. So the OLS estimates bias upward by simultaneity, presumably because relative skill supply increased relatively more in states with greater skill premium. From the model implications, the elasticity of substitution between high and low-skill workers is about 1.87, when assuming no state dependence. As noted in section 3, factors that raise the productivity of high-tech goods have a positive impact on the skill premium if and only if $\sigma > 1$. Given $\sigma > 1$, the estimate for relative innovation is positive and significant. So the results are internally consistent with the model.

However, these estimates could be biased if states with more able workers select themselves into a more skilled-sector. In particular, Bartel and Sicherman (1999) provide compelling evidence that indicates the sorting of more able workers into high-tech industries is the key explanation for the positive correlation between industry wages and technological change. Therefore, my next task is to account for sector allocation in our instrumental variable regression.

5.3 Sector Allocation

A number of approaches can be used to estimate the model. I choose a multi-step estimation procedures.[21] The procedure is implemented as follows.

Step 1. First Stage: Estimate the sector allocation model separately for men and women using log-odds. In the two-sector baseline case, the dependent variable is the log of the ratio of the fraction of workers in the high-tech sector to the fraction of workers in the low-tech sector.

Step 2. Obtain the predicted sector proportion and generate aggregate relative skill supply using equation (2).

Step 3. Second Stage: The instrumented relative skill supply from step 2 is used in the estimation of skill premium, equation (18).

Note that standard errors based on a two-step OLS method differs from those in the 2SLS method. Besides, my relative skill supply measure is generated from four separate estimates (by gender and sector). For each estimate of relative skill supply, I correct the problem using Greene's approach (2000). I then bootstrap standard errors for the second stage of the estimation.

I next discuss the results for the sector choice-adjusted 2SLS, starting with the second stage estimates.

5.3.1 The Impact of Relative Skill Supply on Skill Premium: A Revisit

In this section I present results from the second stage of the 2SLS regression (Step 3). Column 4 of table 4 shows the instrumental variable estimates in which the log of skill premium is regressed on the set of demand side determinants described in section 4.5 augmented with the measure of relative skill supply, $\widehat{n}_{kt}$, which is instrumented by the initial age composition of gender difference in employment. More formally, the estimating equation is

$$\ln(w_{kt}) = \beta_0 + \boldsymbol{\beta}_1' \mathbf{X}_{1kt} + \beta_2 \ln\left(\widehat{n}_{kt}\right) + \boldsymbol{\beta}_3' \mathbf{X}_{2gskt}^{*} + \beta_k + \varepsilon_{kt}, \tag{20}$$

[21] Another method is a full information maximum likelihood, such as the micro anlysis in Heckman and Sedlacek (1985). Results from various Monte Carlo experiments show that results using full information maximum likelihood do not differ significantly from multi-steps estimation (Greene 2000).

where $\ln(w_{kt})$ is log skill premium, and the endogenous regressor is the log of relative skill supply, $\ln(\widehat{n}_{kt})$.

In all specifications, I include a set of share variables $\mathbf{X}_{2gskt}$ as defined above and generate $\mathbf{X}^*_{2gskt} = \sum_{g,s} \mathbf{X}_{2gskt}$ that is gender and sector-specific (i.e. $s = \{H\}$ for a two-state economy, and $s = \{H, L\}$ for a three-state economy), state dummies (β_k), and a complete set of industrial covariates in the demand side ($\mathbf{X}_{1kt}$), which includes a linear time trend, log of relative patent innovation, log of energy price, and log of general purpose machinery price. The coefficient of interest, β_2, measures the effect of the log relative skill supply on log skill premium. The estimate of β_2 in equation (20) has a direct structural interpretation in terms of the model in section 3. It is equivalent to $\frac{(\sigma-2+d)}{(1-d\sigma)}$ in equation (17).

In column 4 of table 4 , I report the estimates from the second-stage of the regression based on the two-state economy. The estimate of the relative skill supply is -0.215, which shows a 65 percent larger negative impacts of the relative skill supply than the baseline results (column 3, table 4). One possible explanation for the upward bias in the baseline case is that high-skill workers are more likely to sort into sectors that provide better matches for their abilities compared to those with low-skills. Sector choice might be more responsive to unobserved skill premiums because differences in unobserved skill prices between the sectors is greater for highly-skilled workers. This could generate a positive correlation between relative skill supply and the error term in the skill premium equation with the presence of selection, and hence an upward bias in the estimation without accounting for sector choice in the relative skill supply.

Because the non-market sector is sizable (about 30 percent), excluding this sector may bias our estimates.[22] In column 5 of table 4, I estimate the model based on a three-state economy. This model raises the estimate of relative skill supply slightly to -0.159. A 10 percent increase in the relative skill supply is associated with about 1.6 percent fall in skill premium.

Assuming no state dependence in innovation in the model, as typically done in the studies on college premium, the estimates imply that elasticity of substitution between high and low skill workers is around 1.79 to 1.84. These estimates straddle right between Angrist's (1995) estimate of around 2 using a natural experiment, and the conventional estimates of about 1.4-1.6 based on partial analyses on college premium. How strong is the induced-bias technology? From section 3, $\sigma > 2$ is needed to obtain the positive long-run effect of an increase in the relative skill supply on skill premium because the skill-biased productivity change induced by the increase in skill-share offsets the downward pressures of the higher skill-share on the skill premium. But the results do not favor the long-run positive effect. The result of 'weak-induced' technological change ($1 < \sigma < 2$, Acemoglu (2001)) implies that changes in the demand for skill is the primary force for the increasing skill premium, consistent with other literature.

Columns 3 to 5 of table 4 indicate that,compared with the OLS results, the IV results give a lower σ and a higher impact of relative innovation. This is the expected bias

[22] Using micro data, Heckman and Sedlacek (1985) pointed out that including the non-market sector gives a better fit to the wage distribution.

produced by the endogeneity of relative skill supply. Without accounting for it, I attribute a higher impact of changes in relative skill supply on skill premium. Once I control for the endogeneity of relative skill supply, part of the impact on skill premium is produced instead by the underlying technological innovation in the model.

In sum, results from all the 2SLS estimations yield a negative supply effect. But which of the two 2SLS results, with or without sector choice, should I believe? I ran a series of Hausman tests (for each patent measure) between the baseline 2SLS specification and the sector-choice corrected 2SLS, and cannot accept the similarity between the two models.

5.3.2 The Impact of Pill Usage on Sector Choice

In this section I report our results from the first stage estimates for females (Step 1). Column 1 of table 5 presents OLS regressions of log relative share of women in the high-tech (vs low-tech) sector on the share of pill usage. Like the regression in the baseline case, all regression models control for the initial age composition of gender differences in employment, state dummies, a set of education shares, the share of pill users (this is dropped for regression on males), and the share non-whites. The regression models also control for the industrial variables from the demand side, including a linear time trend. The share of women who used the pill, the share of population who are non-whites, and the set of education shares are gender and sector-specific.

For illustration purpose, the estimating equation in the two-state economy (high and low-tech sectors) has the following structure,

$$\ln(n_{gkt}) = \alpha_0 + \boldsymbol{\alpha}_1'\mathbf{X}_{1kt} + \boldsymbol{\alpha}_2'\mathbf{X}_{2gHkt} + \boldsymbol{\alpha}_3'\mathbf{M}_{kt} + \alpha_k + u_{gkt}, \tag{21}$$

where n_{gkt} represents the ratio of the proportion of gender g in the high-tech to the low-tech sector in state k and time t, α_k is a set of state dummies, $\mathbf{X}_{1kt}$ represents the set of industrial variables from the demand side, $\mathbf{X}_{2gHkt}$ is a set of education share variables, the share of nonwhites, and the share of pill users in the high-tech sector, $\mathbf{M}_{kt}$ is the set of instruments, and u_{gkt} is an unobserved disturbance.

Compared with the results from column 1of table 5, column 2 shows that after controlling for sector choice, the impact of the proportion of pill-users has greatly reduced: it has only a modest (insignificant) positive effect on the relative proportion of high-tech sector women. Similarly, the impact of the proportion of college and above graduates on sector participation is greatly reduced. These results are consistent with typical selectivity explanation: that able workers are more likely to sort into the sector that provides better matches for their abilities compared to the low-tech sector. So 2SLS estimates are biased upward without conditioning on selection between high and low-tech sectors. Selectivity impacts education more relative to pill-usage.

I next consider a three-sector model: high-tech (H), low-tech (L), and the non-market sector (O). The non-market sector is treated as the reference state. The dependent variable becomes the log of the relative share of women in the high-tech (or low-tech) to the non-market sector. The estimates become significantly positive in both high and low-tech sectors. Column 3 of table 5 shows that a 10 percent more pill-users translates into a roughly 3.4 percentage point rise in the ratio of high-tech to non-market sector population.

This point estimate has a sensible magnitude. The average aggregate proportion of high-tech female employment was about 1.68 times more than the non-market females, and so a 3.4 percent increase in this ratio corresponds to roughly a 6 percent point rise in the high-tech relative to the non-market participation. Using this calculation, I find that the impact on the low-tech sector is 3 percent and is significant. These results indicate that the primary impact of pill usage is to promote labor force participation, and the secondary impact is to encourage a larger portion of women to enter the high-tech sector.

A caveat in these results is that they can be contaminated by the endogeneity of pill usage. In particular, the fraction of women adopting the pill may be affected by three sets of factors. First, it can be affected by birth intention and the extent of sexual activity. Second, it can be affected by social factors such as religious affiliation. The third factor would be idiosyncratic variation that we cannot proxy with our existing data. The first set of factors raises a concern as to whether we are capturing the effect of the pill adoption on relative skill supply, or detecting differential trends in sector choice for people with low-birth intention. Ideally, one could control directly for measures of this set of factors in estimating the relative skill supply, thus exploiting only the variation in the proportion of pill usage coming from religion and idiosyncratic effects. The difficulty I find is that the first set of factors seem to lose their content once viewed at the state-level. So I find the pill adoption issue to be best addressed in future work using individual-level data.

5.4 Wages

In this section, I estimate a parametric wage equation corrected for selectivity bias.[23] In a two-state economy, it amounts to estimating a first generation switching regression models such as Rosen and Willis (1979). In a three-state economy (adding non-participation), the estimation is similar to Lee's approach (1983). I shall estimate both types of economy.

Results from the sector choice regressions set stage for the switching regression. I consider the initial age composition of gender differences in employment to be the exclusion variables in the sector choice regression. The exclusion restriction implied by this instrumental variable strategy is that differentials in gender employment affect females' wages across states only through their impact on sector choice. The log of females' market wage in time t, state k, and sector s is

$$\ln(w_{fskt}) = \gamma_0 + \boldsymbol{\gamma}_1'\mathbf{X}_{4kt} + \boldsymbol{\gamma}_2'\mathbf{X}_{2fskt} + \gamma_t + \gamma_k + \epsilon_{skt},$$

where $\mathbf{X}_{2fskt}$ includes a set of share variables from the sector choice estimations: education shares, the proportion of nonwhites and the proportion of pill users. The variable $\mathbf{X}_{4kt}$ includes the predicted relative skill reward obtained from the last section and the unemployment rate at state-level. The regression also includes a set of time γ_t and state dummies γ_k and an unobserved disturbance term ϵ_{skt}.

[23] Alternatively, I can estimate an empirical model based on more recent semiparametric selecitivity models (e.g. Lee and Ichimura (1991), Dahl (2002)), or numerical simulations. I opt to take the present approach for simplicity. As discussed in Heckman (1990) and Dahl (2002), parametric corrections for selectivity bias perform as well as corrections using semi-parametric methods.

The disturbance term from the indirect utility of the empirical sector choice model in section 5, u, has an independently and identically Gumbel distribution F. A standard normal variate transformation is obtained from $J = \Phi^{-1}F$, where Φ is the standard normal distribution function. Define the set of variables in the sector choice regression as $Z_{skt} = (\mathbf{X}_{4kt}, \mathbf{X}_{2skt}, \mathbf{M}_{kt})$. Because J is a strictly increasing transformation, the alternative s is chosen if and only if $J(\widehat{\boldsymbol{\alpha}}_s' Z_{skt}) > \eta_s^* = J(\boldsymbol{\eta}_s)$, where $\eta_s = \max_s V_{skt} - u_{skt}$. Assuming ϵ_{skt} and $\boldsymbol{\eta}_s^*$ are jointly normally distributed, we have, conditional on the alternative sector s being chosen,

$$\ln(w_{skt}) = \gamma_0 + \boldsymbol{\gamma}_1'\mathbf{X}_{1kt} + \boldsymbol{\gamma}_s'\mathbf{X}_{3skt} - \boldsymbol{\sigma}_s\boldsymbol{\rho}_s\frac{\phi(J(\widehat{\boldsymbol{\alpha}}_s'\mathbf{Z}_{skt}))}{F(\widehat{\boldsymbol{\alpha}}_s'\mathbf{Z}_{skt})} + \gamma_k + \xi_{skt},$$

where $E(\xi_{skt}|s) = 0$, ϕ is a standard normal density, $\boldsymbol{\sigma}_s$ is the standard deviation of the disturbance ϵ_{skt} and $\boldsymbol{\rho}_s$ is the correlation coefficient of ϵ_{skt} and $\boldsymbol{\eta}_s^*$.

The main digression of our model from conventional switching regressions is that the supply side is simultaneously determined with the demand side (sections 6.2-6.3). I first present results that exclude the relative skill reward in both the sector choice and the wage estimations. To proceed, I regress the log odds of sector proportion on the initial age composition of gender differences in employment, the proportion of nonwhites and the proportion of pill users in each sector by state and year, the share of the sample population with college and above (college+), some college, and high-school degrees that are sector, state, and year-specific, the unemployment rate by state and year, and time and state dummies. I then generate a correction function for the wage equation. This is the conventional switching regression model that includes only the supply-side covariates.

Columns 1 and 5 of table 6 report estimates accounting for sector allocation only. The return to pill usage is modest. A 10 percent increase in the proportion of pill users raises wages in the high-tech sector by about 0.5 percent and those in the low-tech sector by 0.3 percent. After including the relative skill reward, the return to pill usage falls by about 30 percent in the high-tech sector and becomes insignificant. One possible explanation for the upward bias in the return to pill usage in the high-tech sector is that pill users are more prone to enter the high-tech sector, as relative skill supply responses elastically to skill premium, the proportion of pill users are positively correlated with skill premium. So, the demand for skill is positively correlated with pill usage and females' wages.

The non-negative return to pill usage in the low-tech sector is consistent with the model prediction that sex-biased technological change that leads fewer but more productive women to remain in the low-tech sector, so the conditional mean productivity is higher (Proposition 3).

Note that the pill estimates are best thought to be the lower bound estimates because the pill has indirect effects via ϕ/F and the relative skill reward. I calculate the total effect of the pill in the high and low-tech sector, which is 0.043 and 0.011 respectively. This is a 16 percent increase in the high-tech sector and a further 27 drop in the low-tech sector. So, the pill has negligible effect for women working in the low-tech sector while it generates moderate (but insignificant) returns to women working in the high-tech sector.

Relative to pill usage, relative skill reward has about 10-fold more impact on women's wages in the high-tech sector. Compared to men, women have slightly less wage impact from relative skill reward, which is nonetheless highly positively significant for both men and women. The discrepancy may reflect unobserved male labor quality that could positively correlate with relative skill reward. Females' unobserved labor quality is partly controlled for using pill usage (recall that I consider the pill to help women utilize their ability more fully). Without controlling for pill usage, the estimate for relative skill reward is biased upward. Because the estimates are similar and significant between the sexes in the high-tech sector, and not significant in the low-tech sector, skill-biased technological change cannot explain the rising gender premium.

The returns to education shows a number of fascinating results. Similar to pill usage, the returns to college+ education show upward bias. When sector allocation and relative skill reward are not included in wage regressions, men have higher returns from college+ education (not shown in table), a result consistent with existing studies such as Blau and Khan (1997). After controlling for sector allocation, the return to college and college + education is higher for women than men in both sectors. More surprisingly, the returns to college+ for men is remarkably sensitive to relative skill reward. All else equal, these results point to the direction that improvements in human capital is the main driving force for women's wage progress.

We then perform Hausman tests to examine the similarity of results with and without considering relative skill reward in the wage regression. The test results do not accept the absence of relative skill reward in the high-tech sector, and do not reject it in the low-tech sector.

In sum, the wage effect of pill usage is moderate and relative skill reward cannot explain the rising gender premium. Improvements in human capital appears to be the main driving force for women's economic progress.

6 Conclusions

I have attempted to evaluate the evidence concerning technological change as an explanation to women's wage progress in the US during 1982-1996 using a simple supply and demand framework. I examine two types of technological change: skill-biased and sex-biased technological change. The latter is dinstinctively different from the former, as I define it as innovation that disproportionately favors women's productivity, such as the contraceptive pill. While skill-biased technological change affects workers' wages through relative skill reward, sex-biased technological change directly enhances women's productive efficiency.

My analysis concludes that the pill has little impact on females' wages when compared to skill-biased technological change. But skill-biased technological change benefits men and women similarly; so it cannot explain the gender premium. However, this result could reinforce, rather than contradicting, existing cross-section findings (Bound and Johnson (1992) and Allen (2001)) that suggested positive impacts of skill-biased technological change on the gender premium. Why? Results from my analyzes using the panel-data structure may pick up the life-cycle aspect of technological change and reflect technological change has become diffused between men and women. Wisdoms from the macro literature, dated back to Kuznets (1955) and more recently Galor and Tsiddon (1997) and Caselli (1999), suggest that technological change first raises inequality and then reduces it because agents typically differ in the rate at which they incorporate new technology. As a result, when a technology, say computer, first arrives, those who are quick to absorb it will increase their earnings and drift apart from their slower counterparts. Eventually, laggards will catch up as the technology becomes diffuse, and earnings disparities decline. If women are vanguards and men are laggards in the adoption of technology, overtime, men catch up with women in adopting technology and skill-biased technological change has little effect on the earnings between men and women.

My supply and demand framework assumes that sex-biased technological change triggers a two-tier sorting system. First, it triggers reallocation of women from low to high-tech sector. Second, seeing an increase in the relative share of ability, R&D firms purposefully direct innovations towards technologies in the high-tech sector that raise relative profitability. Empirical findings in this paper indicate that relative skill supply weakly induces innovation. In addition, though the wage effect of the pill is modest, my results suggest that pill-usage may have important allocative consequences. Pill usage primarily promotes females' labor force participation, and encouragement to the entry into the high-tech sector is secondary. An interesting extension is to integrate women's time allocation decision into the present framework. Exploring the microfoundation of fertility timing and its relation to household labor supply and human capital formation may be some fruitful areas for further study.

Sex-biased technological change is treated as the primitive of the model. Once the possibility of adoption is introduced, many questions posed in this paper, such as 'what is the role of sex-biased technological change in the rise of the high-tech sector?' or 'what is its impact on females' wages?', become ill defined. On a positive note, the model presented should be a useful building block for analyzing general equilibrium implications of technology adoption and other modes of household decisions.

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Year	Age	% in School		% High-Tech Sector		Earnings (pill/no pill)
		no pill	pill	no pill	pill	
1988	20-24	0.17	0.15	0.46	0.46	1.24
	25-29	0.23	0.20	0.53	0.58	1.22
	30-34	0.24	0.15	0.53	0.57	1.12
	35-39	0.20	0.11	0.60	0.55	1
1995	20-24	0.24	0.31	0.45	0.51	1
	25-29	0.08	0.09	0.55	0.63	1.32
	30-34	0.07	0.08	0.59	0.67	1.18
	35-39	0.06	0.03	0.59	0.62	1.18

Table 1. Summary Statistics of the Pill Usage Data, NSFG

Dep. Var: Log(skill premium)	(1)	(2)	(3)	(4)	(5)	(6)
Time	0.012					
	(0.002)					
Log(relative skill supply)	-0.198	-0.333	-0.331	-0.327	-0.140	-0.339
	(-0.226)	(0.271)	(0.236)	(0.280)	(0.310)	(0.206)
Time1		-0.001	0.000	-0.001	-0.001	-0.001
		(0.002)	-0.002)	(0.003)	(0.003)	(0.002)
Time2		0.004	0.007	0.004	0.005	0.011
		(0.002)	(0.003)	(0.003)	(0.002)	(0.003)
Log(energy price)		-0.113	-0.094	-0.112	-0.087	-0.057
		(0.030)	(0.028)	(0.031)	(0.035)	(0.030)
Log(general purpose machinery)		0.317	0.268	0.310	0.203	0.116
		(0.125)	(0.113)	(0.129)	(0.153)	(0.113)
Log(relative patent):						
Generality			-0.150			
			(0.060)			
Originality				-0.086		
				(0.179)		
#Claims					-0.273	
					(0.145)	
Citation Received						0.17
						(0.054)
Constant	-0.113	-1.025	-0.867	-0.985	-0.537	-0.435
	(0.068)	(0.499)	(0.450)	(0.516)	(0.629)	(0.421)
R-square	0.898	0.978	0.981	0.978	0.980	0.985

Huber/White standard errors are in parentheses. Time represents a linear time trend from 1976-96. Time1 represents a linear time trend from 1976-81; Time2 represents a linear time trend from 1982-96. The regressors are linear time trends, the log of relative skill supply, the log of energy price, the log of general purpose machinery price, and four measures of the log of relative patent innovations

Table 2. OLS Estimates: 1976-96 (N=21)

Dep. Var: **Log(skill premium)**	(1)	(2)	(3)	(4)
Log(relative skill supply)	0.255	0.240	0.225	0.140
	(0.210)	(0.163)	(0.186)	(0.215)
Time	-0.019	-0.180	-0.019	-0.013
	(0.008)	0.005	(0.009)	(0.007)
Log(energy price)	-0.132	-0.132	-0.134	-0.111
	(0.020)	(0.016)	(0.032)	(0.020)
Log(general purpose machinery)	1.002	1.008	1.021	0.829
	(0.248)	(0.157)	(0.339)	(0.230)
Log(relative patent):				
Generality	0.021			
	(0.050)			
Originality		0.098		
		(0.184)		
#Claims			0.050	
			(0.201)	
Citation Received				0.052
				(0.046)
Constant	-3.94	-3.892	-4.028	-3.284
	(1.050)	(0.664)	(1.444)	(0.950)
R-square	0.991	0.991	0.991	0.992

Huber/White standard errors are in parentheses. Time represents a linear time trend from 1982-96. The regressors are a linear time trend, the log of relative skill supply, the log of energy price, the log of general purpose machinery price, and four measures of the log of relative patent innovations.

Table 3. OLS Estimates: 1982-96 (N=15)

Dep. Var: Log(skill premium)	1976-96	1982-96			
	OLS	OLS	2SLS	2-sector 2SLS	3-sector 2SLS
Time1	0.000				
	(0.001)				
Time2	0.005	-0.007	-0.001	0.002	0.003
	(0.001)	(0.005)	(0.007)	(0.007)	(0.010)
Log(relative skill supply)	0.060	0.047	-0.130	-0.215	-0.159
	(0.022)	(0.028)	(0.100)	(0.131)	(0.148)
Log(relative patent)	0.023	0.034	0.040	0.047	0.047
	(0.016)	(0.018)	(0.019)	(0.024)	(0.024)
Log(energy price)	-0.0830	-0.114	-0.113	-0.124	-0.124
	(0.016)	(0.020)	(0.025)	(0.024)	(0.029)
Log(general purpose machinery)	0.1780	0.630	0.556	0.456	0.384
	(0.043)	(0.193)	(0.213)	(0.218)	(0.279)
Constant	-0.424	-2.368	-1.974	-1.688	-1.290
	(0.134)	(0.824)	(0.906)	(0.977)	(1.186)
R-square	0.681	0.587	0.600	0.666	0.666

Standard errors are in parentheses. Time1 represents a linear time trend from 1976-81; Time2 represents a linear time trend from 1982-96. The regressors are a linear time trend, the log of relative skill supply, the log of energy price, the log of general purpose machinery price, four measures of the log of relative patent innovations, and state dummies. All regressions are weighted by mean state population.

Table 4. State-Level Panel: Generality as Patent Measure

Dep. Var: Log Odds	2SLS	2-sector 2SLS	3-sector 2SLS	
			High-tech	***Low-tech***
Fraction Pill Usage	0.056	0.036	0.335	0.184
	(0.028)	(0.022)	(0.104)	(0.078)
Fraction College+	1.894	0.654	0.619	0.455
	(0.232)	(0.326)	(0.330)	(0.430)
Fraction some College	1.032	0.659	0.591	-0.324
	(0.252)	(0.333)	(0.418)	(0.614)
Fraction High-School	1.329	0.654	-1.019	-0.354
	(0.218)	(0.326)	(0.433)	(0.624)
Fraction Non-whites	0.022	-0.186	-0.273	-1.060
	(0.170)	(0.166)	(0.532)	(0.515)
Gender Difference in Employment by Age groups:				
	-0.027	0.031	0.021	-0.041
	(0.010)	(0.008)	(0.009)	(0.008)
	-0.032	0.044	0.033	-0.047
	(0.011)	(0.015)	(0.015)	(0.016)
	0.007	0.006	0.018	-0.018
	(0.021)	(0.011)	(0.016)	(0.017)
Constant	-2.189	-4.608	59.899	61.110
	(1.200)	(1.687)	(8.245)	(8.334)
Adjusted-R Square	0.815	0.673	0.409	0.380

Standard errors are in parentheses. The regressors are the initial age composition of gender differences in employment, the share of women who used the pill (this is dropped for regression on males), the share of population who are non-whites, a set of education shares that is gender and sector-specific, state dummies. The regression models also control for the covariates in the demand side, including the log of relative patent innovations, the log of energy price, the log of general purpose machinery price, and a linear time trend. Regressions are done separately for men and women. All regressions are weighted by mean state population.

Table 5. The First Stage Estimates of 2SLS

Dep. Var: Log(wage)	***High-tech Sector***				***Low-tech Sector***			
	women		**men**		**women**		**men**	
Pill Usage	0.050	0.037			0.028	0.015		
	(0.028)	(0.034)			(0.035)	(0.040)		
Education								
college+	0.824	0.575	0.617	0.287	0.858	0.816	0.684	0.605
	(0.209)	(0.206)	(0.167)	(0.129)	(0.150)	(0.163)	(0.175)	(0.139)
some college	0.551	0.339	0.133	0.135	0.282	0.217	0.180	0.096
	(0.251)	(0.224)	(0.154)	(0.170)	(0.111)	(0.114)	(0.107)	(0.146)
high school	0.239	0.275	0.195	0.287	0.211	0.247	0.069	0.044
	(0.200)	(0.216)	(0.225)	(0.209)	(0.148)	(0.124)	(0.098)	(0.114)
Nonwhite	0.130	0.059	-0.031	-0.012	-0.050	-0.019	-0.066	-0.077
	(0.135)	(0.136)	(0.112)	(0.132)	(0.117)	(0.120)	(0.105)	(0.122)
Urate	0.248	0.245	-0.235	-0.355	0.054	0.119	-0.098	-0.126
	(0.178)	(0.184)	(0.226)	(0.239)	(0.226)	(0.223)	(0.177)	(0.184)
Log(skill premium)		0.372		0.403		-0.199		-0.012
		(0.152)		(0.180)		(0.161)		(0.187)
Ancillary parameter								
-Φ/F	-0.752	-0.371	-0.263	-0.217	0.327	0.181	0.022	0.006
	(0.236)	(0.169)	(0.177)	(0.101)	(0.202)	(0.167)	(0.167)	(0.127)
Constant	4.282	4.779	5.982	5.635	5.344	0.237	5.799	5.837
	(0.474)	(0.327)	(0.435)	(0.412)	(0.349)	(0.228)	(0.138)	(0.164)
R-square	0.849	0.853	0.684	0.699	0.742	0.774	0.753	0.767

Standard errors are in parentheses. The regressors in the wage equation include a set of education share variables in sector s, the proportion of nonwhites in sector s, the proportion of women in sector s used the pill, unemployment rate, the predicted skill premium, a selectivity correction term, state dummies, and a linear time trend. All regressions are weighted by mean state population.

Table 6. Estimation Results of the Wage Equation at State-level Panel, 1982-96

7 Data Appendix

7.1 The CPS

Wage and hour-worked data correspond to one year prior to the survey. So the use of 1968-2002 data gives 1967-2001 values. For the employment distribution data, I do not use the 2003 CPS, which is based on 2000 census coding. The 2000 census has a substantially different coding scheme in industry and occupation, making comparisons with categories in prior years difficult.

Basic Sample Selection My samples include men and women aged 25-40 in the year for which the survey was taken, who were not residing in institutional group quarters, and were not employed in farming. Further, the sample includes non self-employed workers in paid nonfarm employment.

Wages Wages are in 1984 dollars, deflated by the CPI All Urban Consumers series CUUR0000SA0. My wage measure is weekly earnings, computed as total wages and salary income earned in the previous year divided by weeks worked in the previous year. Workers with real weekly earnings below $67 in 1984 dollars (equivalent to one half of the 1984 real minimum wage based on a 40-hour week) are excluded. Workers with topcoded earnings are imputed annual earnings at 1.45 times the annual topcode amount.

To minimize sample composition issues, I focus on full-time full-year workers. I define full-time full-year employee as working at least 39 weeks in the prior year and at least 35 hours a week in the survey reference week. Weeks-worked are grouped for survey years prior to 1976. To impute weeks-worked for the 1968-1975 surveys, I use the means of weeks-worked from the 1976-2003 surveys as estimates of weeks-worked for individuals in the corresponding cells in the earlier surveys. All earning statistics are weighted by the March supplemental person weight.

Education Prior to the 1992, the CPS coded respondents' education level according to their highest graded completed. After 1992, highest grade held or degree held was no longer available from the CPS. I define high school graduate as having twelve years of completed schooling, some college attendees as those with any schooling between twelve and fifteen completed years, and college+ as those with at least sixteen years of completed schooling.

The Count Sample The employment data used in section 2.1 are based on the count sample. The count sample is less restrictive than the above wage selection scheme. It uses the basic selection, with the addition that includes workers who worked at least one week in the preceding year, following Katz and Murphy (1992). I consider labor supply as an intensive margin. I calculate total hours worked for each worker by taking the product of total annual hours (weeks worked times usual weekly hours) and the March supplemental person weight. I use the count sample to examine workers' employment distribution by industry.[24]

7.2 The NLSY

I consider sex-biased technological change as contraceptive pill usage. I use the NLSY because it is the only U.S. panel data containing information on females' contraceptive usage.[25] To obtain state-level data, we also use the Geocode data.

The NLSY is a core, nationally-representative, random sample of 12,686 youth cohort who were between the ages of 14 and 22 in 1979. Interviews were conducted yearly from 1979 through 1994; since then data have been recorded biannually. The cross-sectional and supplemental samples consist of 11,774 respondents. Among these respondents, 10,207 were single in 1979; they are the subjects of our analysis. After excluding those who were institutionalized, 9719 respondents (men and women) are left.[26] From these there are 4690 women.

Pill usage data are available biannually since 1982, except that they are also available in 1985. I extrapolate state-level pill usage percentage for odd years as an average of two even years. For example, the percentage of pill usage in 1983 is an average of that in 1982 and 1984. Respondents were asked questions such as 'During the last month, have you used any form of birth control?' and 'What methods have you used in the last month?' I define a dummy as equaling one if a woman uses the pill, and as equaling zero if a woman uses other birth control methods or no method. I then calculate the percentage of women within a state who use the pill.

7.3 The Patent Data

The patent dataset covers January 1, 1963 through December 30, 1999, and includes all utility patents granted during that period, totaling 2,923,922. Each patent document includes the date when the inventor filed for the patent (the application date), and the date when the patent was granted. The actual timing of patented inventions is closer to the application date than to the (subsequent) grant date. So I use the application year as the year of invention.

[24] The industry codes from the CPS changed four times between 1968 and 2002, adding more categories in the latter years. The CPS industry coding is drawn from the census classification: CPS 1968-70 is based on the 1960 census classification scheme; CPS 1971-82 is based on the 1970 census classification scheme; CPS 1983-91 is based on the 1980 census classification scheme; CPS 1992-2002 is based on the 1990 census classification scheme.

[25] One concern about using the NLSY is that the data are cohort data, which differ from other datasets (cross-section) we used in analyses. Vella and Verbeek (1993) examine the representativeness of treating the NLSY as cross-section data. A possible way to resolve this problem, at least partially, is to use contraception data from the National Survey of Family Growth (NSFG). The only drawback is the absence of the state of residence data from its 1982 survey and onwards. As our analysis focuses on state-level, we cannot take advantage of the richness of the NSFG.

[26] This includes respondents who were "aboard ship, barracks", in hospital, jail, other temporary/individual quarters, in on or off-base military family housing, orphanages, or religious institutions.

As the time series moves closer to the last date in the data set, patent data timed according to the application date will increasingly suffer from missing observations consisting of patents filed in recent years that have not yet been granted. As suggested by Hall et al., I use data up to 1997. The sample that I select starts in 1967 to match the CPS series. With these restrictions, 7.5 percent of data are deleted. Because my interest is in studying relative wages in the US, I allow only inventors originating from the US, leaving 1,458,132 observations.[27]

Various measures of the 'importance' or 'quality' of patents are available: the number of claims, citations received, generality (a Herfindahl index of citations received), and originality (a Herfindahl index of self-citation). None of the measures is perfect. For example, there has been patent inflation overtime and there is more citation recently than in the past; but few past citations does not mean that an invention is insignificant. As no single proxy is perfect, it is important to use several alternative measures in the analysis; if similar results are obtained with different measures, I can have more confidence in the reliability of the findings.

In addition, there is no natural scale or value measurement associated with citations data. Standing by itself, the fact that a given patent has received 10 or 100 citations does not tell you whether that patent is "highly" cited. Intrinsically, information on patent citations is meaningful only when used comparatively. But this does not post a problem because I use patent data to proxy for the relative new machine varieties; my patent variable is necessarily relative. For example, I use the ratio of citation received in the high-tech sector to that in the low-tech sector.

I use the mean level of each measure to reveal quality-adjusted patents in high and low-tech sectors, instead of using patent counts. One of the drawbacks of using patent counts as indicators of innovative output is that innovations vary enormously in their qualitative impacts technologically or economically and these differences cannot be captured by count data (Schankerman and Pakes (1984), Griliches (1990)). I follow the categories defined by Katz and Murphy (1992), or as listed in section 4.2, to partition technology categories into high and low tech.

7.4 National Survey of Family Growth (NSFG)

The data files come from the National Center for Health Statistics. I use the National Survey of Family Growth conducted in 1988 and 1995. I do not use the survey in 1976 because they only contain pregnancy data. Nor do I use the survey in 1990 because they contain no information concerning contraception histories.

NSFG is a national representative sample. Each wave contains non-institutionalized women who reported their monthly contraception histories (except in 1982 the survey contains semi-annual data) for the past 4 to 5 years. I utilize data in the 'Respondent' file, which contains information such as contraceptive and marital histories, and other demographics variables. I consider four age groups: 20-24,25-29,30-34,35-39. Women

[27] I find coding errors for the 'state' variable, the coding of "US", "GU", "CZ", "AS", and "PR" are deleted. These symbols do not match CPS state codes or standard FIP codes. I exclude DC and Virgin Islands.

who were pregnant are deleted from the sample. Data on earnings come as interval data. I take the mid-point of the interval to calculate earnings premium.

Because I have multiple observations of contraceptive histories in a given year, I use the scheme below to determine the birth control method of a given year:

1. if only one method was used, that will be the birth control method;
2. if more than one methods were used, I choose the the mode of the birth control method. For example, if a woman used the pill for 4 months and condom for 5 months, condom was the method;
3. if there were ties, I choose the method used earlier.

Because black and Hispanic women were over-sampled, I use sample weight in all my calculations. Note also that analysts must be cautious about codings, which are inconsistent among different waves.