A Dynamic Equilibrium Model of the U.S. Wage Structure, 1968-1996

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March, 2007
Revised March 2009

Abstract: We develop an overlapping generations equilibrium model of the U.S. labor market, and fit it to PSID data from 1968-96. Prior work that attempts to explain changes in the wage structure over this period using equilibrium models has only allowed a few types of labor to be imperfect substitutes in production (e.g., college vs. high-school, males vs. females). Our main innovation is a much finer distinction among types – i.e., we differentiate by 1-digit occupation, education, gender and age, giving 160 types of labor. This is important, as prior work has shown that wage and employment patterns over the sample period differ across occupation-education-gender-age groups in complex ways not captured by simpler models.

As just one example, wages of high-school females either rose or held steady in all four Census 1-digit blue collar occupations over the sample period. But wages of high school males fell substantially in these same occupations. A similar pattern holds for services. These patterns are difficult to explain if high-school men and women are perfect substitutes in production.

Our model provides a rather good fit to both wages and occupational choices for narrowly defined types over the whole 29 year period, while also explaining college attendance rates (something that prior work in the wage structure literature has usually taken as exogenous). Having shown that our model can account for changes in the wage structure at a rather fine level of detail, we use it to assess factors driving those changes.

Acknowledgements: This paper draws heavily on the first chapter of Mathew Johnson's dissertation at Yale. Conversations with John Roemer were instrumental in developing this project. We thank Lance Lochner and Donghoon Lee for providing very useful comments. We also thank participants at the 2007 Analytical Labor Economics Conference in Chicago and the 2007 Labor Econometrics Workshop in Wellington. Keane's work on the project was supported by Australian Research Council grant FF0561843.

I. Introduction

There is a vast literature on the evolution of the U.S. wage structure over the past 40 years. By "wage structure," we refer to patterns of wage differentials across demographic groups, usually characterized by education, gender, occupation and age. The most widely noted change over this period was the growth, since roughly 1976, of the College/High-School wage premium, despite growth in the relative supply of college graduates. In the early 90s, the consensus view of the profession attributed this growth in relative wages of more highly skilled labor to "skill biased technical change" (SBTC) that drove up the rental price of skill *in general*.[1]

But the consensus began to crack in the early 2000s. Card and DiNardo (2002) and Eckstein and Nagypal (2004) look at the wage structure in more detail, examining not just the college premium, but also: (i) the college premium by age, (ii) gender and race gaps, (iii) relative wages across occupations, (iv) wage/experience profiles by education and gender, etc.. In doing so they find many patterns that SBTC alone cannot explain. Other factors must also be at work.[2]

For example, Card and Lemiuex (2001) noted that the increase in the college premium is concentrated among young workers, and that this could be explained by reduced relative supply of young college graduates. But, as they note, it is puzzling why the supply of young graduates stagnated even as the college premium soared in the 80s. Clearly, to explain changes in wages and in education/employment choices *simultaneously*, one needs an equilibrium model.

With this motivation, we build an equilibrium model with labor differentiated along the 4 dimensions of interest noted above (education, occupation, gender, age), and with 5 key sources of change in the wage structure (SBTC, capital-skill complementarity,[3] occupational demand shifts, demographic changes, changing tastes for work and college). We seek to explain changes in wages and employment over the 1968-1996 period at a detailed level using this model.

Our work differs from (most) earlier work in this area in three key ways: First is the fine distinction among types of labor, and the attempt to fit data patterns by narrowly defined type. Second is the inclusion of several factors that may drive changes in the wage structure (i.e., most earlier work looks at one or two factors at a time – most often SBTC and supply shifts). Third is

[1] See, e.g., Bound and Johnson (1992), Katz and Murphy (1992), Murphy and Welch (1992), Juhn, Murphy and Pierce (1993), Berman, Bound and Griliches (1994), Gottschalk and Moffitt (1994). Describing the consensus of the literature, Card and DiNardo (2002) state that "The recent rise in wage inequality is usually attributed to skill-biased technical change," and that "the recent inequality literature reaches virtually unanimous agreement."

[2] Interestingly, however, it should be pointed out that Katz and Murphy (1992), one of the earliest papers in the literature, noted that SBTC alone could not account for the narrowing of the male/female wage differential.

[3] Krusell, Ohanian, Rios-Rull and Violante (2000) and Fallon and Layard (1975) favor this story over SBTC.

the equilibrium nature of the analysis, accounting for both labor supply and college attendance.

With few exceptions, the prior literature on the evolution of the wage structure has been descriptive and/or partial equilibrium in nature. It has not attempted to build equilibrium models that can explain the evolution of the wage structure, while simultaneously explaining educational and employment/occupational choices. The notable exceptions are Heckman, Lochner and Taber (1998a, b) – henceforth HLT – Lee (2005) and Lee and Wolpin (2006a, b) – henceforth LW.

The main distinction between our work and earlier equilibrium models is that we allow many more types of labor to be imperfect substitutes in production. In HLT, there are two types of labor - college and high-school. In contrast, Lee (2005) differentiates labor by both education and occupation (white vs. blue-collar), to get four types. In Lee and Wolpin (2006a, b) there are 6 types that are imperfect substitutes in production (3 occupations in both the goods and service sectors). LW also differentiate labor by education, gender and age, but these types differ only in tastes and/or skill levels – unlike here, they are perfect substitutes in production.

Notably, HLT and Lee obtain opposite answers to the question of how an increase in the supply of college labor affects the college wage premium. HLT estimate a large effect while Lee finds it is negligible. The difference arises because HLT do not model substitution between education types within occupations, while, at the other extreme, Lee assumes education types are *perfect* substitutes within occupations. Obviously ones' assumptions about substitutability among types of labor make a big difference when assessing the role of supply vs. demand factors in changing the college premium (as well as other aspects of the wage structure). Thus, to address such questions, we feel it is important to allow for as many types of labor as possible, and to allow for as flexible a pattern of substitution between types as possible.

Even prior work on the wage structure that is partial equilibrium or descriptive in nature has, for the most part, looked at only a few types of labor, often differentiated only by education, or by very broad skill groups.[4] But as Card and Lemieux (2001), Card and DiNardo (2002) and Eckstein and Nagypal (2004) show, a broad perspective may lead one to miss more subtle patterns that are key to understanding what drives changes in the wage structure. They stress the importance of looking at education, gender, age and occupation. The importance of occupation in particular has been stressed by Kambourov and Manovskii (2004a, b, 2005), Moscarini and Vella

[4] An exception is Katz and Murphy (1992), who, in part of their analysis, looked at labor differentiated into 64 education, gender and age cells, and in another part looked at labor differentiated by industry and 3 broad occupations. This allowed them to see that SBTC could not explain movements in the male/female wage gap.

(2002) and Kranz (2006). They argue occupation is a better measure of skill than education, and that occupational demand shifts are crucial for understanding changes in the wage structure.[5] This motivates us to: (i) differentiate labor by occupation and (ii) allow for occupational demand shifts. As we will show, our model does a good job of explaining wage changes by occupation.

To anticipate a key finding, an awkward fact for the pure SBTC hypothesis is that, while wages and employment of high-school males began to fall in the mid-70s, high-school females did well on both dimensions. Eckstein and Nagypal (2004) note the importance of this pattern. Our model explains it by (i) imperfect substitution of genders, (ii) a demand shift toward (heavily female) service occupations, and (iii) technical change favoring women within occupations.

Notably, Lee and Wolpin (2006b) explain the increase in relative wages of women as resulting from (a) an exogenous decline in fertility, and (b) a shift in demand towards service occupations. This leads to skill upgrading – women to expect to work more, which leads them to acquire more human capital. However, males and females are perfect substitutes in production in their model. We expect such a model may have difficulty explaining the increase in relative wages of women <u>within</u> education/occupation cells that we find is a key feature of the data. This is another motivation for our finer differentiation among types of labor in production.

Thus, our main goal is to estimate an equilibrium model of the labor market with many more types of labor than in prior work. Specifically, we differentiate labor by education (college vs. high-school), gender, age (four ten year intervals from 25 to 64), and by ten occupations (roughly the 1-digit level). This gives 2·2·4·10=160 types of labor, that enter a multi-level nested CES aggregate production technology. The greater richness of the model may lead to a more reliable assessment of what factors were important in driving changes in the wage structure.

We fit our model to PSID data from 1968-1996 on (annual) wages and employment of each of the 160 types of labor. In addition, for each cohort of 19 year-old youth from 1968 to 1990, we fit the fraction of males and females from each of four parental background types who choose to attend college. A key challenge for our model is to explain the stagnation, noted by Card and Lemieux (2001), of college attendance rates in the 70s and 80s despite the rising college wage premium. As see in Figures 2-4, the model does a good job of tracking this pattern.

[5] Kambourov-Manovskii and Kranz both present evidence that returns to occupation (given education) grew much more than returns to education (given occupation) during the 80s and 90s. Kambourov and Manovskii present evidence that occupational mobility increased in the PSID during the 80s and 90s. They infer that the variance of occupation specific labor demand shocks increased, and argue this can explain most of the increase in wage inequality. Moscarini and Vella (2002), however, find that occupational mobility did not increase in the CPS.

And, in most cases, the model also does quite a good job of tracking the wage and employment paths for all 160 types of labor over the 29 years of our data (see Figures 5-16).

The rest of the paper is organized as follows: Section II presents our model, and Section III describes the PSID data used in estimation. Section IV discusses estimation results, including elasticities of substitution between different types of labor. Section V discusses the fit of the model, and in so doing describes many interesting patterns in the data. Section VI concludes.

II. An Overlapping Generations Equilibrium Model of the Labor Market

In each year the population of the model economy consists of overlapping generations of individuals aged 19 to 64. Youth enter the economy at age 19 and decide whether or not to attend college. At that point, there are 8 types of people, differentiated by gender and four levels of parental education, i.e., whether the best educated parent's completed education was less than high-school (<HS), high school (HS), some college (SC) or college (COL). These 8 types have different "costs" of college attendance. The competitively determined college earnings premium determines the proportion of each type that attends. Thus, the supply of college labor is endogenous. We describe the decision rule for college attendance in detail in Section II.3.

All individuals (regardless of their schooling decision) enter the labor force at age 25.[6] After that, a worker's type is determined solely by gender, age and own education (i.e., parents' education no longer matters).[7] In each year (through age 64) workers choose between the home sector or working in one of ten (roughly 1-digit) occupations. Workers make occupational choices based on the current vector of competitively determined occupational wages, which is education-gender-age specific.[8] Workers also have type-specific non-pecuniary payoffs to each occupation. We describe the occupational choice decision rule in detail in Section II.2.

Given the occupational choice decision, the model contains 160 types of labor that are assumed to be imperfect substitutes in production. Types are distinguished by education (college vs. high school), gender, age (4 categories) and occupation (10 categories). These 160 types of labor, along with the aggregate capital stock, are combined, via a nested CES production

[6] We assume work starts at age 25 because, as Geweke and Keane (2000) describe, the sporadic collection of schooling data in the PSID requires one to wait until a person is roughly age 25 to get an accurate read on their completed schooling level. If non-college types work more than college types at ages earlier than 25 this will cause us to somewhat overstate the college lifetime earnings premium. But this should be largely subsumed in the intercept of the college attendance decision rule, and so should have little impact on our results.

[7] This is consistent with results in Geweke and Keane (2000) who find, using a sub-sample of these same data that parental background is insignificant in earnings functions that control for education.

[8] That is, there is no learning-by-doing or on-the-job human capital investment in the model.

function, into aggregate output. We describe the production function in detail in Section II.1.

In each year, the equilibrium of the economy is a 160-vector of occupation-education-age-gender specific wages such that the market for each skill type clears. Let $X_{g,e,a,t}$ denote the type (g, e, a)-specific aggregate supply of labor to the economy at time t, where g denotes gender, e denotes education and a denotes age. This is governed by the sizes, gender composition and educational choices of past cohorts. Let $L_{g,e,a,k,t,}$ denote the type (g, e, a)-specific supply of labor to occupation k at time t. This is governed by the function $D_k^{g,e,a}(.,.)$:

$$L_{g,e,a,k,t} = D_k^{g,e,a}\left[\left\{w_{g,e,a,k,t}\right\}_{k=1}^{10}, X_{g,e,a,t}\right] \tag{1}$$

which says the supply of (g, e, a) labor to occupation k depends on wages $\{w_{g,e,a,k,t}\}_{k=1,10}$, aggregate supplies $\{X_{g,e,a,t}\}$, and group specific tastes for occupations (and the home sector).

Equilibrium wages are given by partials of the aggregate production function, evaluated at the aggregate capital stock A_t and the type specific labor aggregates $\{L_{g,e,a,k,t}\}$:

$$w_{g,e,a,k,t} = f_{L_{g,k,e,a,t}}\left(A_t, \{\{\{\{D_k^{g,e,a}[\{w_{g,e,a,k,t}\}_{k=1}^{10}, X_{g,e,a,t}]\}_{k=1}^{10}\}_{g=1}^{2}\}_{e=1}^{2}\}_{a=1}^{4}\right) \tag{2}$$

Thus, at the equilibrium wage vector, individual labor supply decisions give type specific labor supplies to occupations that equate wages to marginal products for each type in each occupation.

Solving for equilibria in all years from 1968-96 is an iterative sequential process. In each year, the equilibrium wage vector solves a 160-dimensional fixed point problem. We must solve these problems sequentially; i.e., the solution in 1968 determines the supply of college labor that enters in 1974, etc..[9] We present the solution procedure in Web Appendix A. The solution serves as input to estimation, which we discuss in Section II.5 after describing the model in detail.

II.1 Form of the Production Technology

The model incorporates imperfect substitution among labor inputs via a nested CES production function with several levels. One might order CES nests of labor differentiated by occupation, education, gender and age in many ways, but we view our ordering as natural. We place occupations in the upper level nests, as labor of multiple occupations must typically be combined to produce products or services – not necessarily labor of different education, gender or age levels. We felt education should come next, as it seems intuitive that education is the

[9] In this process, the initial 1968 distribution of types of labor $X_{g,e,a,1968}$ is taken as exogenously given. Then, X evolves as a result of the demographics and educational choices of incoming cohorts. Indeed, because of our assumption that the cohort of youth that makes college choices at age 19 in 1968 will not enter the labor market until age 25, we actually take X to be exogenously given up until 1974. (Note: By 1996 the 1968 cohort reaches age 47).

primary determinant of the quality of an occupation's workers. The ordering of gender vs. age is not so obvious. We chose to put gender next and age last, and the model fits well that way.

At the top level, aggregate output depends on capital (A) and CES aggregates of "skilled" and "unskilled" labor, denoted EMP_s and EMP_u, respectively. Thus we have:

$$Y = f\left(\cdot\right) = \beta\left[\lambda_s\left(\lambda_A A^{\rho_s} + \left(1-\lambda_A\right)EMP_s^{\rho_s}\right)^{\frac{\rho_u}{\rho_s}} + \left(1-\lambda_s\right)EMP_u^{\rho_u}\right]^{1/\rho_u} \tag{3}$$

where β = (exp(b(0) + b(1) · t) is a scale and technical progress (TFP) parameter. The λ are "share" parameters that govern income shares for each input, while the ρ ($\rho < 1$) govern the elasticity of substitution between inputs. Note the λ only translate literally into income shares in the Cobb-Douglas special case that arises if $\rho \to 0$ (see Arrow et al (1961)).

The elasticity of substitution between capital and skilled labor, which are nested together, is $\sigma_s = 1/(1- \rho_s)$, while that between the capital-skill composite and unskilled labor is $\sigma_u = 1/(1-\rho_u)$. We have capital-skill complementarity, meaning growth in the capital stock increases demand for skilled relative to unskilled labor, if $\rho_u > \rho_s$, which implies $\sigma_u > \sigma_s$. Our top-level setup is similar to that in Fallon and Layard (1975) and Krusell et al (2000), except we define skill along occupational rather then educational lines.

At the second level nest we have skilled (EMP_s) and unskilled (EMP_u) labor aggregates:

$$EMP_s = \left(\lambda_1 EMP_1^{\rho_H} + \left(1-\lambda_1\right)EMP_2^{\rho_H}\right)^{1/\rho_H} \qquad EMP_u = \left(\lambda_u EMP_{u1}^{\rho_L} + \left(1-\lambda_u\right)EMP_{u2}^{\rho_L}\right)^{1/\rho_L} \tag{4}$$

Skilled labor combines labor in occupations 1 and 2 (professionals and managers). Unskilled labor combines labor in the service and blue-collar occupations, EMP_{u1} and EMP_{u2}, respectively.

At the next level, the service sector input (EMP_{u1}) is a CES aggregate of employment in occupations 3-6 (technicians, sales, clerical and (narrow) services), while the blue-collar input (EMP_{u2}) is a CES aggregate of employment in occupations 7-10 (craftsmen, operatives, transport operatives, and laborers). These are constructed as follows:

$$\begin{aligned} EMP_{u1} &= \left(\lambda_3 EMP_3^{\rho_{u1}} + \lambda_4 EMP_4^{\rho_{u1}} + \lambda_5 EMP_5^{\rho_{u1}} + \left(1-\lambda_3-\lambda_4-\lambda_5\right)EMP_6^{\rho_{u1}}\right)^{1/\rho_{u1}} \\ EMP_{u2} &= \left(\lambda_7 EMP_7^{\rho_{u2}} + \lambda_8 EMP_8^{\rho_{u2}} + \lambda_9 EMP_9^{\rho_{u2}} + \left(1-\lambda_7-\lambda_8-\lambda_9\right)EMP_{10}^{\rho_{u2}}\right)^{1/\rho_{u2}} \end{aligned} \tag{5}$$

Thus, the parameter ρ_{u1} governs substitution among the four service sector occupations, while ρ_{u2} governs substitution among the four blue-collar occupations.

Next we consider occupation level effective labor inputs. Each occupational labor input is assumed to consist of an aggregate of college and high school labor, as follows:

$$EMP_k = \left(\mu_k HS_k^{\rho_e} + (1-\mu_k) COL_k^{\rho_e} \right)^{1/\rho_e} \qquad \text{for} \qquad k=1,10, \tag{6}$$

where HS_k and COL_k denote high school and college type labor in occupation k, respectively. Note that the CES share parameters μ_k are allowed to vary across the ten occupations, but the education substitution parameter ρ_e is assumed to be common to all occupations.

At the next nesting level, the amounts of college and high school labor supplied to each occupation are assumed to consist of male and female workers. Thus we have:

$$\begin{aligned} HS_k &= \left(\xi_k \left(HS_k^{male} \right)^{\rho_g} + (1-\xi_k)\left(HS_k^{female} \right)^{\rho_g} \right)^{1/\rho_g} \\ COL_k &= \left(\gamma_k \left(COL_k^{male} \right)^{\rho_g} + (1-\gamma_k)\left(COL_k^{female} \right)^{\rho_g} \right)^{1/\rho_g} \end{aligned} \qquad \text{for} \qquad k=1,10. \tag{7}$$

The elasticity of substitution between genders is common across occupation /education cells, and is governed by the parameter ρ_g. But the share parameters ξ_k and γ_k are allowed to differ by both occupation and education level.

The final CES nest aggregates labor in four different age groups: 25-34, 35-44, 45-54 and 55-64. These aggregate up to the four gender/education level inputs as follows:

$$HS_k^{male} = \begin{pmatrix} \tau_{1k} \left(HS_{k,25-34}^{male} \right)^{\rho_a} + \tau_{2k} \left(HS_{k,35-44}^{male} \right)^{\rho_a} + \tau_{3k} \left(HS_{k,45-54}^{male} \right)^{\rho_a} + \\ (1-\tau_{1k}-\tau_{2k}-\tau_{3k})\left(HS_{k,55-64}^{male} \right)^{\rho_a} \end{pmatrix}^{1/\rho_a} \tag{8a}$$

$$HS_k^{female} = \begin{pmatrix} \sigma_{1k} \left(HS_{k,25-34}^{female} \right)^{\rho_a} + \sigma_{2k} \left(HS_{k,35-44}^{female} \right)^{\rho_a} + \sigma_{3k} \left(HS_{k,45-54}^{female} \right)^{\rho_a} + \\ (1-\sigma_{1k}-\sigma_{2k}-\sigma_{3k})\left(HS_{k,55-64}^{female} \right)^{\rho_a} \end{pmatrix}^{1/\rho_a} \tag{8b}$$

$$COL_k^{male} = \begin{pmatrix} \nu_{1k} \left(COL_{k,25-34}^{male} \right)^{\rho_a} + \nu_{2k} \left(COL_{k,35-44}^{male} \right)^{\rho_a} + \nu_{3k} \left(COL_{k,45-54}^{male} \right)^{\rho_a} + \\ (1-\nu_{1k}-\nu_{2k}-\nu_{3k})\left(COL_{k,55-64}^{male} \right)^{\rho_a} \end{pmatrix}^{1/\rho_a} \tag{8c}$$

$$COL_k^{female} = \begin{pmatrix} \varpi_{1k} \left(COL_{k,25-34}^{female} \right)^{\rho_a} + \varpi_{2k} \left(COL_{k,35-44}^{female} \right)^{\rho_a} + \varpi_{3k} \left(COL_{k,45-54}^{female} \right)^{\rho_a} + \\ (1-\varpi_{1k}-\varpi_{2k}-\varpi_{3k})\left(COL_{k,55-64}^{female} \right)^{\rho_a} \end{pmatrix}^{1/\rho_a} \tag{8d}$$

The degree of substitutability between age groups is common across occupation/education/ gender cells, and is governed by the single parameter ρ_a. But the share parameters τ_k, σ_k, ν_k and ϖ_k are allowed to differ by occupation/gender/education level.

As is standard in the wage structure literature, we let the share parameters vary over time to capture SBTC and other factors that shift demand for different types of labor. Specifically, we let them follow low order polynomials in time, using logistic transformations to constrain them to lie in the (0, 1) interval. For example, in the top level nest (equation (3)), we specify that:

$$\lambda_i = \frac{\exp\left(\lambda_{i0} + \lambda_{i1} t + \lambda_{i2} t^2 + \lambda_{i3} t^3 + \lambda_{i4} t^4\right)}{1 + \exp\left(\lambda_{i0} + \lambda_{i1} t + \lambda_{i2} t^2 + \lambda_{i3} t^3 + \lambda_{i4} t^4\right)} \qquad i = s, A \tag{9}$$

Thus, the capital share parameter λ_A and the capital/skilled labor aggregate share λ_s are allowed to follow 4th order polynomials in time. Similar expressions apply to the other share parameters.

As we'll see below, 4th order polynomials provide a good fit to the data. This is perhaps not surprising, for two reasons. First, if technical change, or shifts in relative demand for different types of labor, do occur, it is plausible they occur gradually over time. Second, while the share parameters may also be affected by short run macro shocks, it is notable that the sample period contained only two large macro shocks – the severe recessions of '74-75 and '82.[10] Thus, it seems plausible that low order polynomials would be adequate to capture most demand shifts induced by technical change or major macro shocks over the sample period.

One detail left to discuss involves the share parameters for the different age groups, in equations (8a)-(8d).[11] There are 120 such parameters. If each were allowed to follow a 4th order polynomial, it gives 600 parameters. To avoid such proliferation of parameters, we impose two restrictions: (1) Occupations within each of the three broad occupational skill groups (i.e., skilled labor, services and blue collar) have common intercepts in their time polynomials. This reduces the number of polynomial intercepts from 120 to 36. (2) The linear and higher order terms in the polynomials are assumed to be common across all ten occupations within each of the 12 education/gender/age groups. This reduces the number of such terms from 480 to 48.[12] Also, in many cases we found that 4th order polynomials were not necessary to obtain an adequate fit to the data. In these cases we stopped at the 3rd order.

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[10] Besides that, there were three much milder recessions in 69:4-70:4, 80:1-80:3 and 90:3-91:1.

[11] Equations (8a)-(8d) each contain four share parameters that must sum to one. Thus, they contain three free parameters that must lie between 0 and 1. We impose this constant using a multinomial logit transformation. The same is true of equation (5).

[12] Assumption (2) means that if the income share of an age group within a gender/education category rises in one occupation it will tend to rise in all occupations. This does not mean income shares of gender/education groups will move similarly across occupations. How gender and education shares move is determined by parameters in (3)-(7).

II.2 Occupational Choice

In each period, workers aged 25 to 64 choose among 11 alternatives (10 paid occupations and home work). Recall there are 16 types of workers, distinguished by age-gender-education, and each type faces a different 10-vector of occupational wages. Types also differ in tastes for working in each occupation. Workers choose among the alternatives based on the wage vector and their tastes. [13] The utility to a worker conditional on choice of occupation k is given by:

$$U(g,e,a)_{k,t} = \alpha_{0,g,e,k} + \alpha_1 w_{g,e,a,k,t} + \alpha_2 \left(e - \overline{e}_{k,t}\right)^2 + \alpha_3 \Pr\left[d_{k,t-1} = 1\right] + \varepsilon_{k,t} \qquad (10)$$

Here, $\alpha_{0,g,e,k}$ is a non-pecuniary reward that a worker of gender g and education level e receives in occupation k. This is assumed to be age and calendar time invariant. In the second term, α_1 is a parameter and $w_{g,e,a,k,t}$ is the wage for a worker of type (g, e, a) in occupation k at time t.

The third term is the difference between a worker's own education level and the average level of workers in occupation k. This captures that workers may receive a psychic benefit (cost) from working with other workers who are similar (different) to themselves.[14] In the fourth term, $d_{k,t-1}$ is a 1/0 indicator for whether occupation k was chosen at t-1. Thus, Pr[$d_{k,t-1}$=1] is the proportion of workers who chose occupation k in the previous year. This is included to capture persistence in occupational choices.[15] Finally, the taste shock $\varepsilon_{k,t}$ is assumed to be iid extreme value. This gives simple multinomial logit (MNL) forms for the choice probabilities.

The utility of the home alternative differs by age, gender and calendar time as follows:

$$U(g,e,a)_{0,t} = \alpha_{h0} + \alpha_{h1} \cdot t + (\alpha_{h0,f} + \alpha_{h1,f} \cdot t) \cdot I\left(g = f\right) + \tilde{\alpha}_{g,a} + \varepsilon_{h,t} \qquad (11)$$

Here α_{h0} and α_{ht} capture the level and trend in the value of home time for men, while $\alpha_{h0,f}$ and $\alpha_{h1,f}$ capture deviations in the level and trend for women. We expect level and trend differences by gender, given the initially much lower but rapidly rising level of female employment over the sample period. Of course, the trend for women arises not just from changes in tastes, but also from changes in fertility and marriage market opportunities, which we do not model explicitly.

Note that the model has multiple means to explain increasing employment of women, not just changing "tastes" in (11). For instance, there may be technical change or demand shifts that

[13] As wages depend only on gender, education and age – and not on accumulated occupation-specific or general work experience – workers do not need to consider any impact of current choices on future wage offers.
[14] We include this effect because we believe it exists – e.g., college workers are willing to give up some earnings for more mentally stimulating employment. If it exists and we ignore it, labor supply elasticities will be biased down.
[15] Persistence may arise due to habit persistence, or labor adjustment costs at the individual or aggregate level.

drive up income shares for the service sector occupations, leading in turn to higher wages in (10). Or there may be female biased technical change within occupations (equation (7)).

The term $\tilde{\alpha}_{g,a}$ is a vector of gender/age specific deviations in the value of home time. These are meant to capture the lower market participation rate of older workers (as they retire). Finally, $\varepsilon_{k,t}$ is again an independent type I extreme value error term.

Given the setup in (10)-(11), the proportions of workers of type (g, e, a) who choose to work in occupation k, or who choose the home sector 0, are given by the MNL expressions:

$$\mathrm{P}\left(d_{kt}=1 \mid g,e,a\right)=\exp\left(U(g,e,a)_{k,t}\right)\Big/\sum_{k=0}^{10}\exp\left(U(g,e,a)_{k,t}\right) \quad \text{for} \quad \mathrm{k} = 0,10 \tag{12}$$

We are now in a position to state the specific form of supply function in equation (1):

$$L_{g,e,a,k,t} = D_k^{g,e,a}[\{w_{g,e,a,k,t}\}_{k=1}^{K}, X_{g,e,a,t}] = \mathrm{P}(d_{kt}=1|\mathrm{g,e,a})\cdot X_{g,e,a,t}. \tag{1'}$$

II.3 Educational Choice

At age 19, the members of each entering cohort decide whether to attend college. Then, at age 25, they enter the labor market, as either college or high-school workers. Recall that youth differ in parental background, denoted by $b \in$ {<HS, HS, SC, COL}and gender g. The value function associated with college attendance for a youth of type (g, b) is given by:

$$\begin{aligned} V_t^C(g,b) &= [\phi_{1m} I\left(g=m\right)+\phi_{1f} I\left(g=f\right)]\cdot E\left[\sum_{a=25}^{64}\delta^{a-25}w_{g,COL,a}\right]-\phi_{2b} + \\ &\left(\phi_3+\phi_4 t+\phi_5 t^2\right)I\left(g=f\right)+\left(\phi_6 t+\phi_7 t^2\right)I\left(g=m\right)+\phi_8 Cost+\varepsilon_{C,t} \end{aligned} \tag{13}$$

Here, $E\left[\sum_{a=25}^{64}\delta^{a-25}w_{g,COL,a}\right]$ is the expected present value of lifetime income (from age 25 to the end of the working life at age 64) for college workers of gender g. The second term, ϕ_{2b}, is a cost of college that is specific to the youth's parental background type b.[16] The terms ϕ_3 through ϕ_7 accommodate differences in tastes for college between males and females, as well as allowing for quadratic trends in these tastes.[17] The term *Cost* is a measure of tuition costs, and $\varepsilon_{c,t}$ is a type I extreme value error. The $\varepsilon_{c,t}$ capture unobserved heterogeneity in costs-of/tastes-for college.

There are two critical things to note about $E\left[\sum_{a=25}^{64}\delta^{a-25}w_{g,COL,a}\right]$. First, youth take this

[16] This is similar to HLT, except they define types using AFQT quartiles instead of parents' education.

[17] College graduates also receive the expected PV of non-pecuniary rewards for the occupations they expect to work in (the $\alpha_{0,g,e,k}$ in equation 10), which differ from those of high school graduates. As the $\alpha_{0,g,e,k}$ are time invariant, and occupational choice probabilities vary slowly, these present values will be largely be subsumed in the ϕ parameters.

expectation assuming the current period equilibrium wage vector will persist into the future. This is a key simplifying assumption that differentiates our work from HLT and LW, who assume youth forecast the future path of equilibrium wages. Our assumption makes model solution much simpler, which allows us to have many more types of labor that are imperfect substitutes.[18]

Second, the expectation is taken using the probabilities in (12) to integrate over work and occupational choices a person of type (g, COL) is likely to make over the life cycle. E.g., women tend to have lower expected earnings than men because they tend to spend less time employed.

The coefficient on expected PV of earnings, ϕ_1, differs between males and females. The constant ϕ_3 and trend terms ϕ_4 and ϕ_5 also shift the value of college for women. These terms account for gender differences in tastes for college. They also capture in a simple way the idea that, relative to men, more of the return to college for women may come in the marriage market than in the labor market (see Keane and Wolpin (2009)).

The "cost" terms ϕ_{2b} for $b \in$ {<HS, HS, SC, COL} capture the fact that youth from different social backgrounds face different psychic and monetary costs of college. For instance, youth with less educated parents may be less prepared for college, so attendance would require greater effort. They may also have less of a taste for education, because it was not inculcated in their youth. As for monetary costs, while (13) contains a tuition variable, this fails to capture other costs of college such as room and board. Nor does available data capture financial aid well. And even accurate cost data would not capture the fact that less educated parents provide less financial support for youth to attend college (see Leslie (1984), Keane and Wolpin (2001)).

Finally, the value associated with stopping school at the high school level is given by:

$$V_t^{HS}(g,b) = \left(\phi_{1m} I\left(g=m\right) + \phi_{1f} I(g=f)\right) \cdot E\left[\sum_{a=25}^{64} \delta^{a-25} w_{g,HS,a}\right] + \varepsilon_{HS,t} \tag{14}$$

This value function again involves the expected PV of lifetime earnings, in this case for workers with a high school education. We do not repeat any other terms from (13), as ϕ_{2b} through ϕ_7 can all be interpreted as utilities or costs of college attendance *relative* to stopping at high school.

[18] We see no philosophical reason to prefer assuming youth forecast future wages. Even the assumption they know the current wage structure exactly is strong (see Manski (1993), Dominitz and Manski (1996) and Betts (1996) for evidence on what youth know about wages). Rational expectations (as in LW) or perfect foresight (as in HLT) are often invoked not because we literally believe them but because they make model solution simpler. But here, if youth forecast future wages, it vastly increases computational difficulty. In Lee and Wolpin (2006a, b), only 6 rental prices need to be forecast (as there are 6 types), but even then they can only solve for an approximate equilibrium. Some recent work by Martins (2006), using surveys of Portuguese college students, suggests that: "students have a relatively good understanding of [current] market [wage] rates." He argues for the same assumption we make here.

Given (13) and (14), the probability a youth of type (g, b) decides to attend college is:

$$\mathrm{P}_t\left(e = COL \middle| g,b\right) = \frac{\exp(V_t^C(g,b))}{\exp(V_t^{HS}(g,b)) + \exp(V_t^C(g,b))} \tag{15}$$

After the college decision, workers enter the labor market at age 25. Then, wages are influenced only by a worker's education, age and gender (parental background no longer matters).[19]

Given (15), the number of college workers of gender g entering the economy at time t is:

$$COL_{g,t}^{25} = \sum_{b=1}^{4} N_{g,b,t-6}^{19} \cdot \mathrm{P}_{t-6}\left(e = COL \middle| g,b\right) \tag{16}$$

Here $N_{g,b,t-6}^{19}$ is the number of 19 year olds of gender g and parental education b who enter the model at time t-6. We take these entering cohort sizes, which vary substantially over time (see Figures 3-4), as <u>exogenous</u>. This is important for identification (see Section II.5).

Ignoring mortality,[20] the stock of 25-34 year old college workers evolves as follows:

$$COL_{25-34,t}^{g} = COL_{25-34,t-1}^{g} + COL_{25,t}^{g} - COL_{35,t}^{g} \qquad \text{for} \qquad g{=}male, female$$

Stocks of college and high-school workers in the other age groups evolve in the obvious way.

II.4 Equilibrium Determination of the Capital Stock

We estimate two versions of the model, with capital treated as exogenous or endogenous. In the latter case, the capital stock at t is determined by equating the marginal product of capital evaluated at current factor input levels to the exogenous rental price of capital r_t^C. Formally,

$$r_t^C = \partial Y_t(A_t, \{\{\{\{L_{g,e,a,k,t}\}_{g=1}^{2}\}_{e=1}^{2}\}_{a=1}^{4}\}_{k=1}^{10}) \big/ \partial A_t \tag{17}$$

r_t^C can be thought of as a world price of capital not determined in the model (that is, it does not depend on model factor supplies). It is assumed to evolve over time according to the polynomial:

$$r_t^C = c_0 + c_1 t + c_2 t^2 + c_3 t^3 + c_4 t^4 \tag{18}$$

In estimating this version of the model, we also fit the capital stock data from 1968-1996.

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[19] While apparently strong, this assumption is consistent with the huge literature on "Mincer" earnings functions, where log earnings are typically specified as a function of education and "potential" experience (i.e., age – education – 6), and parental background characteristics are rarely controlled for. Interestingly, one of the few studies to include them, Geweke and Keane (2000), found parental education was insignificant after conditioning on age and own education. On the other hand, Keane and Wolpin (2001) found a strong correlation between parental education and a person's skill level at age 16. The two results can be reconciled, however, by noting that in Keane and Wolpin the skill "endowment" at age 16 largely drives college attendance decisions. The analogous finding in our model would be that the $\{\phi_{2b}\}$ are key drivers of these decisions.

[20] Attrition from the economy is also incorporated, using life tables, but we ignore it here to simplify notation.

II.5 Summary and Discussion of Identification ands Estimation

The exogenous capital model given by (1)-(16) has 306 parameters, and the endogenous capital model that adds (17)-(18) has 311. Of these, 237 are in the share equation polynomials, 9 are substitution parameters, and 2 are TFP parameters, giving 248 technology parameters in all. The occupational choice model contains 46 parameters, of which 33 are gender/education specific tastes for occupations. The college choice equations contain 12 parameters.

Fitting the model to the PSID data is an iterative process. Starting with a trial parameter vector, we first solve for the equilibrium of the economy in each year. Given the sequence of 29 annual equilibria, the model generates 160·29·2 predicted values of type (g, e, a)-specific wages and labor supply to each occupation over the 29 years, and 8·23 predicted college attendance rates for the 8 gender/parent education types over 23 years.[21] Parameters are updated to achieve the best fit to these 9464 data elements via the method of moments (see Web Appendix A).

The parameters are clearly over-identified. The model attempts to match income shares for 160 types of labor over 29 years. If share parameters varied *freely* across years we could fit shares perfectly, regardless of how the substitution parameters ρ_s, ρ_u, ρ_H, ρ_L, ρ_{u1}, ρ_{u1}, ρ_e, ρ_g and ρ_a are set, so substitution elasticities would not be identified. But we constrain the share parameters to lie along low order polynomials in time. This allows identification of substitution elasticities. Low order polynomials provide a good fit, implying the shares do vary slowly over time.

Furthermore, the model also attempts to match occupational employment shares for each (g, e, a)-kind of labor in each of the 29 years. We could fit to these shares perfectly, *regardless* how other model parameters are set, if group specific tastes for each occupation (the $\{\alpha_{0,g,e,k}\}$ in equation (10)) could vary freely over time. This would leave effects of wages on occupational choice unidentified. Instead, we constrain these parameters to be constant over time and age.[22]

Within this constrained structure, substitution elasticities are identified by how wages or income shares respond to variation in the supply of workers of different types over time. To gain intuition, it is useful to consider a CES production function with only two inputs, skilled labor (L_{St}) and unskilled labor (L_{Ut}). This generates the following equation for relative wages (w_{St}/w_{Ut}):

$$\ln\left(w_{St}/w_{Ut}\right) = \ln\left(\lambda_{St}/(1-\lambda_{St})\right) - (1-\rho)\ln\left(L_{St}/L_{Ut}\right) + \varepsilon_t\,, \quad (1\text{-}\rho)<0, \qquad (19)$$

where the elasticity of substitution σ=1/(1-ρ). In our framework *technology* (or demand) shocks

[21] We only fit college attendance rates up through 1990 because the 1991 cohort doesn't finish school until 1997.
[22] Only tastes for home vary by time and age – see equation (11).

affecting wages are captured by the $ln[\lambda_{St}/(1-\lambda_{St})]$ term (the ratio of CES share parameters, which captures SBTC or other demand shifts). If one can adequately control for the technology term $ln[\lambda_{St}/(1-\lambda_{St})]$, then the error ε_t captures only error in measuring relative wages and employment using finite samples of workers. In that case one can consistently estimate ρ in (19) by OLS. Otherwise, ρ confounds the effect of supply-induced movements along the demand curve with shifts in demand, and one must instrument for $ln[L_{St}/L_{Ut}]$ using exogenous labor supply shifters.

Katz and Murphy (1992) estimate a version of (19) by OLS, where L_{St} and L_{Ut} are college and high school labor. They assume the SBTC term $ln[\lambda_{St}/(1-\lambda_{St})]$ follows a linear trend. (As we have noted, if shares were allowed to vary *freely* over time ρ is not identified). The linear trend gives a good fit to the data for 1963-87. They estimate SBTC of 3.3% per year, and σ=1.41. For their estimates to be consistent, it is essential that SBTC does follow a linear trend. Given our longer period (1967-96) and finer differentiation of labor, we find the CES share parameters must be allowed to follow 3rd or 4th order time trends to provide a good fit to the data.

There remains a concern that ε_t is contaminated by high frequency demand shocks, in which case we should instrument for $ln[L_{St}/L_{Ut}]$ or estimate the demand function jointly with a labor supply model. HLT instrument using cohort size, but we do joint estimation. Our supply model (i.e., the college and occupational choice equations) has several sources of exogenous variation in labor supply.[23] Most notable is variation across cohorts in their size and in the distribution of gender/parental education types, denoted $\{N^{19}_{g,b,t-6}\}$ in Section II.3. Thus, while past work typically treats cohort size (and hence parent's fertility) as exogenous with respect to current demand shocks, we assume that parents' education is exogenous as well. This is equally plausible. Furthermore, parent education is a good predictor of own education and occupation.

Note that parental education rose substantially, but gradually, across cohorts – see Figures 3-4. This exogenously shifts the number of male and female college graduates in each cohort, which in turn shifts occupational choices. Substitution elasticities are identified by how such exogenous (low frequency) supply shifts affect relative wages (or income shares).[24]

[23] Even if our trends adequately capture movements in the $ln[\lambda_{St}/(1-\lambda_{St})]$, so ε_t captures only measurement error, it is desirable that our supply model contain sources of exogenous variation in $ln[L_{St}/L_{Ut}]$. Otherwise, demand shocks are the only source of variation in $ln[L_{St}/L_{Ut}]$, and the two regressors in (19) would be perfectly collinear, were it not for functional form. This would be analogous to estimating a selection model with no exclusion restriction.

[24] Also note that changes in current wages cannot influence current supplies of college graduates by gender/age, as these are pre-determined by age 19 college choices.

III. Data

The model is fit to occupation specific wages and employment shares for each gender-education-age group from 1968-96, and college attendance rates for each gender-parental education group from 1968-90. We also require data on the capital stock and cohort sizes.

III.1 Occupational Employment Shares and Earnings

The data on occupational choices and wages are constructed using the core representative sample of the Panel Study of Income Dynamics (PSID), which began collecting data on 5000 families in 1968. We aggregate the individual earnings and occupation data up to the 160 gender-education-age-occupation cells used in our model, using the PSID core sample weights.[25]

A drawback of the PSID is that it is smaller than the Current Population Survey (CPS), leading to more noise in estimates of occupational earnings and employment shares. *But the key advantage of the PSID is the consistency of its occupational coding*. Occupations are classified by 1970 Census codes for the whole 1968-96 period. In contrast, the CPS changed occupational codes several times. Consistency in occupational classifications is crucial to our analysis.[26]

We define ten occupations, based primarily on 1970 Census 1-digit codes. But in a few cases we disaggregate using 3-digit codes. Most notably, we felt the "Professional, technical, and kindred workers" category covered too wide a skill range. We split it into "Professionals" and "Technicians" using 3-digit codes (see Web Appendix B); e.g., dentists are "professionals," and dental technicians are "technicians." Thus, our ten occupations (codes in parenthesis) are:[27]

High Skilled Occupations:

1. Professionals (selected from 001-195, see Web Appendix B)
2. Managers and Administrators (201-245)

Service Occupations (Unskilled Group 1):

3. Technicians (selected from 001-195, see Web Appendix B)
4. Sales Workers (260-285)
5. Clerical and Kindred Workers (301-395)

[25] We screen observations with unassigned education, or invalid or missing occupation or employment, as well as observations with positive hours and no earnings, or missing/zero hours and positive earnings.

[26] While the PSID uses 1970 Census codes throughout, the level of detail in describing occupations varied over time. From 1968-73 and 1975, only 1-digit codes were recorded. In 1974, 3-digit codes were recorded. 2-digit codes were recorded from 1976-80, and 3-digit codes were recorded thereafter. In 1999 the PSID released the *Retrospective Occupation-Industry Supplemental Data Files*. This relied on original written interview descriptions of respondents' occupations to assign 3-digit occupation codes back to 1968.

[27] We dropped some occupations with consistently low employment: farmers, farm laborers and supervisors, private household workers and armed forces personnel. The self-employed with no reported occupation were also dropped.

6. Service Workers, except Private Household (901-965)

Blue Collar Occupations (Unskilled Group 2):

7. Craftsmen and Kindred Workers (401-600)

8. Operatives, Except Transport (601-695)

9. Transport Equipment Operators (701-715)

10. Laborers, Except Farm (740-785)

Labor income and work hours are assigned to occupations using a respondent's main occupation. We cannot see how annual income and hours are divided among occupations. This leads to potential misclassification if a worker works in multiple occupations in a year. However, a problem only arises if the worker switches *between*, not *within*, our ten occupational categories.

The employment data fit by the model are the number of *full-time equivalent* workers in an occupation in a given year, and the earnings to be fit are average annual earnings of such a full-time equivalent worker. To count full-time equivalents (FTEs), we must decide how many hours define full-time. For example, say we define a full-time professional as working 2400 hours per year. Then, a worker whose main occupation is in the professional category, and who reports working 1600 hours, contributes 0.75 units of labor (of his/her type) to that sector in that year. He/she also contributes 0.25 units of time to the home sector.[28] Of course, how we define full-time hours is merely a scale normalization that has no bearing on the substantive results. Web Appendix C explains in detail how we define full-time hours, and how we construct occupational employment shares and earnings. Earnings are expressed in 1999 CPI-U dollars.

III.2. College Attendance Rates

A simplifying assumption of our model is that there are two education types, those with a high-school education or less (HS) and those who attend college (COL), regardless of whether they complete it. The use of two broad categories is similar to HLT. Given the PSID's focus on household heads and spouses, information on college attendance of youth is scant. Thus rather than checking if a youth attended college at, say, ages 18-22, we can gauge attendance more accurately by looking at age 25, and seeing if a person reports having attended earlier. [This data limitation is the primary motivation for our assumption that youth make educational decisions at age 19 and enter the labor market six years later at age 25.] Even then, some waves of the PSID do not ask highest grade completed, so college attendance must be inferred from other questions.

[28] Thus, the number of FTEs assigned to home consists not only of workers who are fully unemployed or out of the labor force, but also includes some fraction of the time of part-time workers.

For example, a respondent might say he/she completed high school, and also report school attendance at later ages. From this we would infer the person had attended some college.

We fit college attendance frequencies by cohort (from 1968-90), separately by gender and parental education (<HS, HS, SC and COL), as measured by the highest level of education completed by either parent. We construct the college attendance rate for a cohort that enters at age 19 in year *t* as follows: Using all individuals aged 24-26 in year *t*+6, we form an indicator for whether each person attended college. We then form a weighted average of these indicators, using the PSID core weights, within each gender/parental education group. We use the three-year age window because, as indicated above, the PSID college attendance data is not ideal. Using the window reduces noise, as more observations are used to calculate the choice frequencies. Of course, this smooths variation in college choice over time, but we felt this tradeoff was sensible, given that our model is not meant to predict very short-run movements in college attendance.

Our tuition cost variable is from NCES (2003), Table 315, and covers in-state tuition and required fees for both two and four-year institutions. This is meant to capture the average tuition level faced by those deciding on college attendance. The data is not adjusted for grant and other financial aid, nor does it include indirect costs such as room and board or commuting (note that HLT share the same limitation). We do not include data on aid because, unfortunately, such data are only available for 1987 onward (from NCES National Post-Secondary Student Aid Study).[29]

III.3. Other Variables: Cohort Size, Attrition and the Capital Stock

Our overlapping generations model requires as inputs (i) the age 25 to 64 distribution of the population by gender and education in 1968, and (ii) the cohort sizes of age 19 entrants from 1969-90 (by gender and parental background). We use Census data to measure both. Thus, to arrive at our 1968 inputs, the age/education choice proportions computed using the PSID are used to divide each Census age cohort into HS and COL subgroups. Hazard rates from the 1970-1990 U.S. Decennial Life Tables provide attrition rates for each age group. Model inputs are not updated to account for immigration over the period. (HLT find immigration effects are small).

For our capital stock measure we use BEA estimates of nonresidential fixed investment, reported in June 2003. We add equipment and software (E&S) and non-residential structures (omitting government and residential fixed assets). Details are provided in Web Appendix C.

[29] A few studies, such as Leslie (1984), use aid data collected by the Cooperative Institutional Research Program (CIRP). CIRP collects institution-reported bracketed data on financial aid for full-time freshmen reaching as far back as 1967. However, this data is not publicly available, and it may not be directly comparable to the NCES data.

IV. Estimation Results

We fit our model to the PSID data using the method of moments (MOM). Estimation is computationally burdensome: at each trial parameter value we must solve for a 160-dimensional fixed point in each of 29 years. As our focus is on substantive results, we describe the solution algorithm and the MOM estimator in Web Appendix A. As noted earlier, we estimate two versions of the model, with physical capital treated as exogenous or endogenous. Interestingly, parameter estimates and model fit are very similar in each case. Thus, to conserve on space, we primarily report on the estimates and evaluation of model fit for the exogenous capital model.[30]

IV.1. Parameter Estimates – Production Technology

IV.1.A. Production Function – Substitution and TFP Parameters

We begin with Table 1, which reports the substitution and TFP parameters. At the highest level CES nest (equation (3)), we estimate the elasticity of substitution between physical capital and skilled labor is 0.47, while that between the capital+skilled labor aggregate and unskilled labor is 3.23. As 3.23>0.47, the estimates imply capital-skill complementarity, consistent with the findings of Fallon and Layard (1975) and Krusell et al.[31] It should be remembered, however, that we define skilled labor based on occupation while they define it based on education.

Moving down to the next level (equation (4)), we estimate that the skilled occupations (professionals and managers) are highly substitutable in production (i.e., σ_H=6.25). But for the two unskilled aggregates (services and blue collar), substitution is rather inelastic (σ_L=0.56). This is intuitive (e.g., it is easier to substitute an engineer for a manager than a plumber for a nurse).[32]

At the next level (equation (5)), we estimate substitution elasticities among the four blue-collar occupations that form the blue collar aggregate, and for the four service occupations that form the service sector aggregate. In each case, we cannot reject that substitution is unit elastic (as ρ_{u1} and ρ_{u2} do not differ significantly from zero – either statistically or quantitatively).

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[30] The endogenous capital model, which has 5 additional parameters, also provides a slightly better fit.

[31] Our substitution elasticity between skilled labor and capital (0.47) is similar to Krusell et al's (0.67). But our elasticity between the capital-skill composite and unskilled labor (3.27) is higher than their's (1.67), implying even stronger capital-skill complementarity. This may be because in (3) we define skill based on occupation rather than education. However, when we endogenize capital, we obtain an elasticity of 1.75, which is nearly identical to theirs.

[32] These elasticities are less precisely estimated than those in the top-level nest. This occurs for two reasons: (1) Our sources of identifying variation (i.e., changes in the size and "quality" – in terms of parents' education – of entering cohorts) predict variation in skilled vs. unskilled labor aggregates better than labor supply to more narrowly defined occupations, as one would expect. (2) The estimated elasticity of substitution between professionals and managers is very high (6.25). As we'll see in Fig. 10 and 14, wages of managers and professionals move quite closely together. This would be true for a wide range of elastcities – so long as they are high – making the precise elasticity both hard to pin down and, for the same reason, rather irrelevant. The same issue arises with age elasticities (see below).

The next level (equation (6)) describes substitution between college and high school labor *within* occupations. We obtain 1.6, which is close to estimates in the prior literature (which, as HLT note, are centered on 1.4 to 1.5). However, our figure is not directly comparable to those in the prior literature, which has not differentiated labor by both education and occupation. In order to obtain the elasticity between college labor *in toto* and high school labor *in toto* (as opposed to *within*-occupation), we must simulate an exogenous increase in the supply of college labor.[33]

As we note in Table 2, simulations of our model imply substitution elasticities for high school and college labor in the range of 1.15 – 1.26.[34] This is well below the elasticity of 1.6 we obtained for high school and college labor *within* a one-digit occupation, but it is still well within the range of the prior literature (e.g., HLT obtain 1.26 when they instrument for the college/high-school labor supply ratio using cohort sizes). It is intuitive that different education levels are more easily substitutable within occupations (e.g., a high-school educated manager could substitute more easily for a college educated manger than could a high-school educated laborer).

The next lower nest (equation (7)) describes substitution between males and females (*within* education and occupation cells). We estimate that this elasticity is very high (5.26). Thus, male and female workers appear to have very similar skills, conditional on education/occupation. On the other hand, we can also simulate the elasticity of substitution between male and female workers *in toto*. As we see in Table 2, when we do this, the range of elasticities is 1.85-2.20. Thus, not surprisingly, male and female workers appear much less similar unconditionally.

At the bottom level (equation (8)) we estimate substitution among age groups conditional on the gender/education/occupation cell. Our estimates of this elasticity were very high, and the algorithm had a hard time pinning down a final value. So we decided to peg it at 10. This gives unconditional elasticities in the 4 to 4.5 range, comparable to Card and Lemiuex (2001).

Finally, the estimate of $b(1)$ at the bottom of Table 1 implies TFP growth of 0.4% per year (Note: the BEA estimates TFP growth over the 1968-96 period of 0.55% per year).[35] Remaining output growth is due to growth of capital and labor, including growth in labor quality due to increasing education and shifts toward more skilled occupations.

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[33] That is, we simulate a "helicopter drop" of college workers, increasing the number of such workers at each age by the same proportion. These new workers choose occupations in the same way as workers do normally in the model.
[34] The elasticity of substitution between two inputs which appear in a 2nd or lower level nest, depend on the share parameters in all common higher nests. As these share parameters vary over time, so will the substitution elasticities. Thus, for inputs like high school and college labor, we cannot give a single elasticity figure, but a range of figures.
[35] See "Multifactor Productivity Trends, 1997," at www.bls.gov/schedule/archives/all_nr.htm#PROD3. We may obtain a smaller estimate of TFP growth because our model better captures skill upgrading of the labor force.

IV.1.B. Production Function – Share/Productivity Parameters

As noted in Section II.1, we let the share parameters vary over time according to cubic or quartic trends. There are 237 polynomial parameters. Given the large number, we do not report them here, but instead present them in Web Appendix D, Tables D1 to D4. As polynomial coefficients are not very informative, we also report implied values of the share parameters for three selected years: 1968, 1982 and 1992. Of course, to the extent that CES substitution parameters depart from zero (i.e., from Cobb-Douglas), the "share" parameters are not exactly equal to income shares. However, their trends over time tell us how demands for (and income shares of) the various groups move. Some interesting patterns emerge from the estimates:

First, in Table D1, while the share of the capital+skilled labor composite rises from 1968 to 1982, it falls back to its original level by 1996. (Nor does the skilled labor share within the capital+skilled labor composite increase). Thus, a general increase in the return to skill does not explain the rise of the college premium over this period. This is consistent with recent papers like Card and DiNardo (2002) and Eckstein and Nagypal (2004) who argue *a simple trend in the share of skilled labor cannot explain changes in the wage structure* over the 70s-90s. As we'll see, shifts in demand across occupations (and for groups within occupations) are more important.

Second, the share of the Service occupations (relative to blue collar) rises substantially. This implies increased demand for female labor, as women are more likely to choose that sector.

Third, in Table D2, which reports the shares of high school vs. college workers *within* occupations, we see that the high school share falls substantially in six of the ten occupations: managers, sales workers, service workers, craft workers, operatives, and laborers. It falls more modestly for professionals and technicians. (Only for clerical workers and transport operatives does it stay flat.) Thus, a shift in demand toward college labor is clearly a key factor (along with capital skill complementarity) in explaining the rise of the college wage premium.

Fourth, in Table D3, which reports gender shares, we see the share of high-school males (relative to high-school females) falls in all ten occupations. The college male share falls in 8 out of ten. Together, the 2^{nd} and 4^{th} patterns – growing demand for labor in the Service sector and demand shifts toward female labor *within* most occupations – can explain both (i) closing gender wage and employment gaps, and (ii) the fact that high-school females fared much better than high-school males over the 1969 to 1996 period.

Finally, Table D4 reports age group shares. These are very stable, but there is a weak upward trend for the younger age group (25-34) among all females and college males.

IV.2. Parameter Estimates – Occupational Choice

Table 3 reports on the occupational choice equation. The coefficient α_1 on the annual wage is .0000862. This implies a labor supply elasticity *to a single occupation* of about 4 to 6; and a labor supply elasticity to the economy as a whole of roughly .74 for both high-school and college males (the equality is a coincidence), and 1.13 and 0.94 for college and high-school women. Details of these calculations are provided in Web Appendix E. These elasticites are important for how the model explains changes in the wage structure: they influence the extent to which wage increases in a sector or occupation are "choked off" by increased labor supply.

Next, the estimate of α_2 implies that workers get a psychic benefit from working in an occupation where other workers have education similar to their own. And the estimate of α_3 implies the existence of mobility costs. As a result, the increase in labor supply to an occupation resulting from increased labor demand will not be fully realized within one period.

The next panel of Table 3 reports the non-pecuniary payoffs from working in each of the ten occupations for each of the four gender/education types. These fall into predictable patterns. For instance, women (whether high-school or college educated) have a preference for clerical and service (i.e., "pink collar") occupations and a relative distaste for being laborers.

Table 3 Part B reports parameters related to the value of home time. As expected, females have a positive intercept shift ($\alpha_{h0,f}$ =2.02), so they have higher utility in the home sector than males. But they also have a negative time trend ($\alpha_{h1,f}$ = -.028). Thus, a declining value of home time (presumably due to declining fertility) explains part of the increase in female labor supply over this period. Of course, part is also explained by increasing demand for female labor (see Section IV.1.B). Finally, the table reports age effects in the value of home time ($\alpha_{g,a}$). As expected, these are increasing with age. This is in part how the model explains retirement.

IV.3. Parameter Estimates – Educational Choice

Table 4 reports estimates of the college choice equation. Figure 1 helps to interpret the estimates. It presents, for each cohort of 19 year olds from 1968-96, the expectation, at the time of their college choice, of the PV of lifetime income for college vs. high school workers. These are calculated using the wage structure at the time of the choice, along with equation (12), which gives occupation and home choice probabilities, and with δ=.95. For males, Figure 1 says the (perceived) college lifetime <u>earnings</u> premium was about \$415k for the 1968 cohort, narrowed to \$330k in the 1974-83 period, widened to \$400k in 1990, and widened further to \$480k in 1996.

The coefficient on the expected PV of lifetime income governs how the college earnings premium influences college attendance. For males, the coefficient ϕ_{Im} is .0000134. This implies an elasticity of supply of college labor with respect to the gain to college of about 3.2.[36] This elasticity is important for how the model explains changes in the wage structure. It governs how quickly an increased college premium is "choked off" by increased supply of college labor.

The coefficient on lifetime income for women ϕ_{If} is half that for men. This is consistent with results in Keane and Wolpin (2009) that half of women's gain to college comes from better marriage market opportunities rather than higher earnings. Affirming this, PV of income gains for women are half those of men (see Figure 1), yet their attendance rate is similar. Women must get more utility from college, or reap gains via a different channel (i.e., the marriage market). As we do not model marriage, the model says women get more utility from college (ϕ_3=4.12).

As expected, the fixed effects for parental education are figure prominently in the "cost" of college. For example, translating into monetary equivalents, the male coefficient on earnings implies the "cost" of college is greater by (4.87-3.82)/(.0000134) = \$78,000 for youth whose parents were high school graduates (HS) vs. those whose parents had some college (SC).[37] The magnitude of these "costs" is large relative to average tuition levels. Thus, the most plausible interpretation is that they primarily capture psychic or effort costs, as discussed in Section II.3.

For males, the time trend for tastes is small, implying tastes for college were nearly the same in the 90s as in 1968. This is important: the model can explain the puzzle of stagnating male college attendance (despite a rising college wage premium) without resort to declining tastes for college. The key is the 6 to 9 point increase in the home share for males discussed below (Section V). This counteracts the increasing college <u>wage</u> premium, so the lifetime <u>earnings</u> premium actually falls (from \$415k in 1968 to \$400k in 1990 – see Fig. 1). With an elasticity of 3.2, this implies a 12% drop in college attendance – about what we see in the data.

For women the situation is reversed. Their college attendance rate fluctuates around 45% throughout the period (see Figure 2), despite: (i) increased demand for female labor (see Section IV.1.B), and (ii) a down trend in returns to the non-market alternative (see Section IV.2). These

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[36] E.g., as shown in Figure 1, in the 1990 cohort, expected PV of lifetime income for male college and high school workers were \$930k and \$530k, respectively, a \$400k difference. In Fig. 2, we see the college attendance rate for males in this cohort was roughly 42%. Say the gain to college increased by 10%, or \$40k. This increases the latent index for college (eqn. (13)) by .54, increasing attendance to 55.4%, a 32% increase (N.B., this is college *attendance* – not completion – and our data has rates as high as 60% (see Fig. 2)). Thus we get an elasticity of 32/10 = 3.2.

[37] Similarly, HLT obtain a large range of \$99,000 in the "cost" to college across their four AFQT types.

factors caused the lifetime income gain from college for women to more than double, from $85k in 1968 to $200k in 1990 (see Figure 1). Thus, to explain why attendance did not increase, the non-market return from college must have fallen. This is what the trend coefficients in Table 4 imply. Presumably this reflects reduced importance of marriage market returns to college.

Finally, the effect of direct tuition costs is found to be small and insignificant. But as we discussed in Section III.2, this variable is a rather poor measure of true college costs.

V. Evaluation of Model Fit to Wage, Employment and College Choice Patterns

We evaluate model fit using Figures 2 to 16. These compare model predictions with PSID data on college attendance, employment and wages. Of course, the PSID data fluctuate from year to year due to the relatively small sample size, which generates noise in the population aggregates. The model has no means to fit high frequency fluctuations (see Section II.5). Thus, our hope is that it will fit broad trends in the data. In general, it appears to do well in this respect.

For example, in Figure 2 we see that the model provides a good fit to the data on college attendance rates by cohort for both males and females. In Figures 3-4, we see it continues to provide a good fit when the data is broken down by gender and parental education. For example, the attendance rate for males with HS graduate parents falls from 60% or more in the late 60s to less than 30% in the 1990 cohort, and the model captures this dramatic downward trend well.

Besides capturing the downward trends in college attendance for all eight gender/ parental-education types, the model also captures level differences quite well. These level differences are substantial. For instance, for males of parental types <HS, HS, SC and COL, college attendance rates in 1990 were 12.6%, 28.7%, 52.2% and 72%. It is not a foregone conclusion that the model would capture both level differences and time trends for all eight gender/parental-education types, as it has no gender/parental-education/time interactions.[38]

Next, Figure 5 reports the fit to employment shares and the home sector, which are also quite good. Visually, the only apparently large discrepancies between model predictions and the PSID data are for clerical workers and the home sector. But the scale of the graphs exaggerates these discrepancies. For home, the vertical axis goes from 30% to 40%, so the seemingly large errors in the late 60s and early 70s are only a few percent. The largest error is in 1975, when the model predicts 36% and the data give 40%. The model captures the roughly 10-point drop in the

[38] Notice that, in Figure 4, college attendance rates trend down for females of all four parental education types. Yet, in Figure 2, we see the college attendance rate for all females stayed flat, at roughly 45%. This is because average education levels of parents rose substantially across these cohorts (as is shown in the dotted lines in Figures 3-4).

home share from 1968 to 1996 quite accurately. Similarly, the largest discrepancy for clerical workers is in the late 60s and early 70s, but this is only about 2 percentage points (10% vs. 8%).

Note that employment shares of professionals, managers and technicians increased substantially, while sales and services were flat. (Thus, most of the growth of the broad service sector was from technicians and clerical workers). The shares of all four blue-collar occupations fell. The model captures all these patterns well, but it understates the growth in clerical workers.

Figure 6 shows the model also fits occupational wages well – both time trends within occupations and level differences across occupations. Again, what appear visually to be some large discrepancies are due to the scale of the graphs. The largest single errors are only about $5,000. This is for professionals in 1994 ($63k data vs. $58k model), managers in 1972 ($58k data vs. $53k model), and technicians in 1973 ($43k data vs. $38k model). Other errors are much smaller, and, given the noise in the data, a few errors of this magnitude are not surprising.

Figures 7 to 14 assess the fit to occupation shares and earnings for each of the four gender/education subgroups. Given the complexity of the patterns, the fit is surprisingly good:

For high school males (see Figures 7-8), two aspects of the data are notable. First, the home sector rises from 15% to 24% during the period.[39] Second, in about 1974 wages start to trend down in all four blue-collar occupations (see lower right panel of Figure 8). The model captures the wage trends quite well. It gets the magnitude of the increase in home about right (i.e., 8% predicted vs. 9% data), but misses the time path somewhat. The occupation with the largest employment share decline is operatives, falling from 16% in 1968 to 10% in 1996, a pattern the model captures almost perfectly (see lower left panel of Figure 7).

Figures 9-10 report results for college males. Their home share increases from 9% in 1968 to 15% in 1996. This is nearly as large as the increase for HS males.[40] Employment shares drop substantially in the professional and clerical occupations, while other occupations are fairly stable. The model captures these patterns well. Of course, the largest occupations for college males are managers and professionals, followed by technicians. In all three, there is a clear down trend in wages for the first half of the sample period, and an upward trend in the second half, with the break point happening in about 1982-1983. By 1996, real wages for college males in these occupations are roughly back where they started in 1968. Thus, for males, the growth in the college wage premium over the period as a whole is clearly due to declining high school wages.

[39] The model predicts the home share for HS males will continue to rise to 34% in 2016, and then plateau.
[40] The model predicts the home share for college males will continues to rise to 19% in 2007, and then plateau.

Only in the post-1982 period do growing college wages contribute to the trend. Beaudry and Green (2005) emphasize the importance of this pattern, which our model captures well.

Next, Figures 11-12 report results for high school females. In contrast to males, the home share *falls* sharply, from about 69% in 1968 to 47% in 1996. The model predicts a decline from 63% to 47%, capturing the trend quite well (aside from overstating home in the early years). The occupations where employment increases most are clerical (9% to 19%) and managers (2% to 7%). The model overstates the share of clerical in the late 60s to early 70s by about 4 points (the flip side of understating home). But it captures the broad upward trend in the clerical sector well.

Occupational earnings paths of high school females diverge sharply from those of high school males. *In almost every occupation they have at least a mild upward trend in wages over the 1968-96 period*. In particular, the three largest occupations for high school females are clerical (19% in 1996), services (10% in 1996) and managers (7% in 1996). In all three, wages trended upward. Third largest is operatives (6% in 1996). Here, wages were quite flat (female wages were flat or mildly increasing in all blue collar occupations). But for HS males, wages fell in all these occupations. The differences are sometimes substantial: e.g., for operatives, wages of HS males fell about 20% while those of females were flat, for managers wages of HS males fell 8% while those of females doubled. It is difficult to reconcile a view that the rising college premium represents simply a general increase in returns to skill – or that males and females are perfect substitutes in production – when HS females did so well relative to HS males.[41] Eckstein and Nagypal (2004) emphasize the importance of this pattern, which our model fits successfully.

Finally, Figures 13-14 report results for college females. Their home share also fell sharply, from 58% in 1968 to 38% in 1996. The model captures this well, predicting a decline from 58% to 35%, and matching the time path quite accurately.[42] The occupations where college women tend to work changed markedly as well. In 1968 the largest occupations by far were technicians (15%) and clerical (14%). As only 42% of college women worked in the market, these occupations comprised 67% of their total employment. During the sample period the share of clerical stayed flat while that of technicians grew modestly to 20%. The occupations that grew most were professionals, from 3% to 9%, managers, from 4% to 9%, and sales, from 1% to 5%.

[41] Part of the relative growth of female wages within education/occupation cells may be due to skill upgrading via increased work experience. Given the increase in female employment rates, and consensus estimates of experience returns, we calculate this mechanism is unlikely to raise relative wages of prime working age women by any more than 5%. Thus, this mechanism seems unable to explain differences of the magnitude we see here.

[42] The model predicts home shares of females will cease declining after 1996. They rise slightly to a plateau of about 37% in 2011 for COL females and 48-49% for HS females. This appears roughly consistent with recent data.

In Figure 14, we see that wages of college women in the professional and managerial occupations trend up throughout the sample period (+33% and +30%, respectively). This is in contrast to the pattern for college men, where, as noted earlier, wages in these occupations trend down until about 1983 and up thereafter, ending in 1996 about where they started. In the clerical occupation wages of college women were flat, while for college males they fell sharply (-20%). And wages of college women grew sharply in sales, while for college men they were flat. The model fits all the patterns in wages and employment for college women quite well. The sharp contrast with patterns for college men is hard to rationalize if genders are perfect substitutes.

Figures 15 and 16 break down the changes in wages of college vs. high school workers by gender and age. For men, we see the striking fact, noted by Card and Lemieux (2001), that the increase in the college premium was concentrated among younger workers. For 25-34 year olds, the college premium increased from 1.33 in 1980 to 1.60 in 1996.[43] But for the other 3 age groups no such trend is apparent. The model captures these patterns quite well.

For women, the situation is somewhat different. For 25-34 year olds, the college premium increased from 1.37 in 1980 to 1.55 in 1996.[44] But the college premium increased for 45-54 year olds as well, from 1.33 to 1.57.[45] But for them, the college premium was roughly 1.76 in 1968, so it actually fell over the sample period as a whole. The other two age groups don't reveal such patterns. Again, the model captures all these features of the data quite well.

Finally, we consider changes in the <u>overall</u> college wage premium, for men and women. The male college premium dropped from about 60% in 1968 to a trough of 37% in 1976, and then rose sharply to about 70% in 1996. For women the premium was 58% in 1968 – similar to that for men – but it behaved quite differently over time. It fell to a trough of 45% in 1974 (well above the 37% for men), rose to a peak of only about 57% in 1987 (well below the 70% peak for men), and then stayed flat from 1988 through 1996 (in contrast to the continued rise for men).[46]

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[43] Note: For 25-34 year old males, average annual earnings for college and high school workers in 1980 were roughly $44,000 and $33,000, a ratio of 1.33. The figures for 1996 are $48,000 and $30,000, a ratio of 1.60.

[44] For 25-34 year old women, average annual earnings for college and high school workers in 1980 were roughly $22,000 and $16,000, a ratio of 1.37. The figures for 1996 are roughly $31,000 and $20,000, a ratio of 1.55. (Recall that these are average wages for each full time equivalent (FTE) worker, so, e.g., women who work full-time count twice as much as those who work part-time when taking the average).

[45] For 45-54 year old women, average annual earnings for college and high school workers in 1980 were roughly $24,000 and $18,000, a ratio of 1.33. The figures for 1996 are roughly $36,000 and $23,000, a ratio of 1.57.

[46] What the college premium did in the 90s is controversial. In the March CPS, Card and DiNardo (2002) find it was flat for males. But Eckstein and Nagypal (2004), Beaudry and Green (2005) and Autor et al (2005) find it continued to increase (but at a slower pace than in the 80s). Results are sensitive to data issues, such as handling of top coded

The model captures these patterns quite precisely. We emphasize that the college premium for women was no higher in 1996 than in 1968. This is embarrassing for the SBTC story (even if augmented to include increasing demand for female labor, as in Katz and Murphy (1992)). SBTC implies an increase in the college premium for women, not just men. The reason the college premium did not rise for women is that, as we have seen, high school women did rather well in terms of wages over this period. *The different behavior of the college premium for men vs. women again highlights the importance of treating them as imperfect substitutes in production in order to explain changes in the wage structure*.

VII. Conclusion

We have developed and estimated an equilibrium model of the U.S. labor market, using PSID data from 1968-1996. A key feature of the model is that many types of labor, differentiated by education, gender, occupation and age (giving 160 types), are treated as imperfect substitutes in production. We show that our model succeeds in fitting many aspects of the changing wage structure that are difficult to explain without treating all these groups as imperfect substitutes:

For example, looking *within* occupation/education cells, wages generally fell for high school men, while rising for high school women. This is difficult to explain if men and women are perfect substitutes in production. Similarly, over the sample period as a whole the college premium rose only for younger males and females (it actually fell for females in the 45-54 age range). This is hard to explain if age groups are perfect substitutes.

Our model also succeeds in fitting a number of patterns that are difficult to reconcile with a simple SBTC story for the changing wage structure (even if augmented to include a demand shift toward female labor). Most notable is that high school females did so well, in terms of both wages and employment, relative to high school males.[47] Indeed, over the period as a whole, the college wage premium rose for men but not for women. This is an embarrassing pattern for the SBTC story as it should imply an increase in the college premium for <u>both</u> women and men.

Our model fits not just wages but occupation employment shares and college attendance rates. With few exceptions, it fits patterns for wages, employment and college attendance rather

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earnings in the CPS, how one constructs wage rates, etc.. Our college premium measure grew more than what these authors report. This is largely because we have only two types of labor, so high school drop-outs are grouped with "high school," and those with post-graduate work are grouped with "college." As Eckstein and Nagypal find, post-graduate wages grew more than college wages, and high school drop-out wages fell relative to high school wages.

[47] As Eckstein and Nagypal (2004) note, this is hard to reconcile with a view that the college premium rose due to a general increase in the skill rental price (especially as the relative supply of high school females rose substantially).

well for all 160 types of labor over the whole 29-year period.[48] It achieves this using five main factors: (i) our CES production function exhibits capital skill complementarity, (ii) trends in the CES share parameters imply increasing labor demand in female dominated service occupations relative to blue collar, (iii) the high school share falls dramatically in six of the ten occupations we examine, and modestly in two others (but <u>not</u> in the Clerical occupation, which is the largest for high school females); thus, a form of SBTC (i.e., increasing relative demand for college labor), is present in most occupations, (iv) demand for high school males (relative to high school females) fell in all ten occupations, while demand for college males fell in eight, and (v) the value of home time fell for women, presumably capturing declining fertility.

Notably, the share of the skilled labor aggregate did <u>not</u> increase, contrary to what a simple SBTC story predicts. Instead, factor (ii) illustrates the point made by Kambourov and Manovskii (2004a, b, 2005) and Eckstein and Nagypal (2004) that *occupational* demand shifts are important for understanding changes in the wage structure. We find *occupation specific* demand shifts for different types of labor are also important (factors (iii) and (iv)). Factor (iv) can be described as "gender biased" technical change. This seems plausible, e.g., automation of production reduces the role of physical strength. But factor (iv) may also capture factors we have omitted, like reduced discrimination, or increased work experience of women within cells.

It is useful to contrast our results with Lee and Wolpin (2006b). In their model, genders are perfect substitutes, so the gender wage gap falls due to <u>skill upgrading</u>: an exogenous decline in fertility and a demand shift toward services led women to expect to work more. So they invest more in human capital. But this may not adequately explain the growth of female relative wages *within* education/occupation cells, or the failure of the college premium to increase for women.[49]

Finally, a success of our model is that, for males, it provides an explanation for the puzzle (noted by Card and Lemieux (2001)) that their college attendance rate stagnated from 1968-90 despite a sharp increase in the college <u>wage</u> premium. And it does so without the need to resort to changing tastes for college. The point is that the expected lifetime <u>earnings</u> premium actually fell from 1968-90, due to declining male labor force participation. This was due, in turn, to declining demand for labor in male dominated occupations.

[48] One might argue that we should fit time paths of wages and employment well simply because we allow the share parameters to follow time polynomials. But we do not include any occupation/education/gender/age interactions. Thus, it is not at all obvious we could obtain a good fit to wage and employment paths for all 160 types of labor.

[49] Increased experience may explain part of the growth of female wages within cells, but in Section V we argued that, given plausible experience returns, it could not explain it fully. Also, employment increased by similar amounts for <u>college</u> and <u>high-school</u> women. So this does not help explain why the college premium did not rise for women.

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Web Appendices are located at: www.business.uts.edu.au/finance/staff/MichaelK/research.html

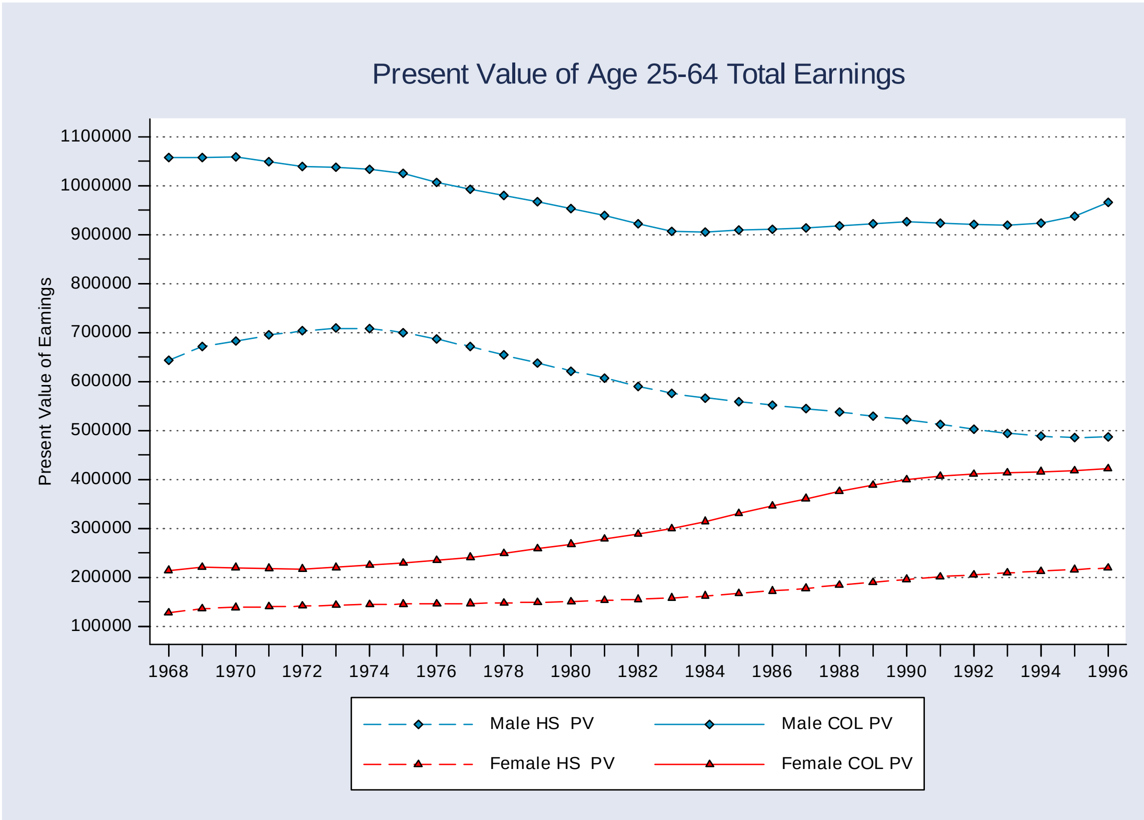


Figure 1

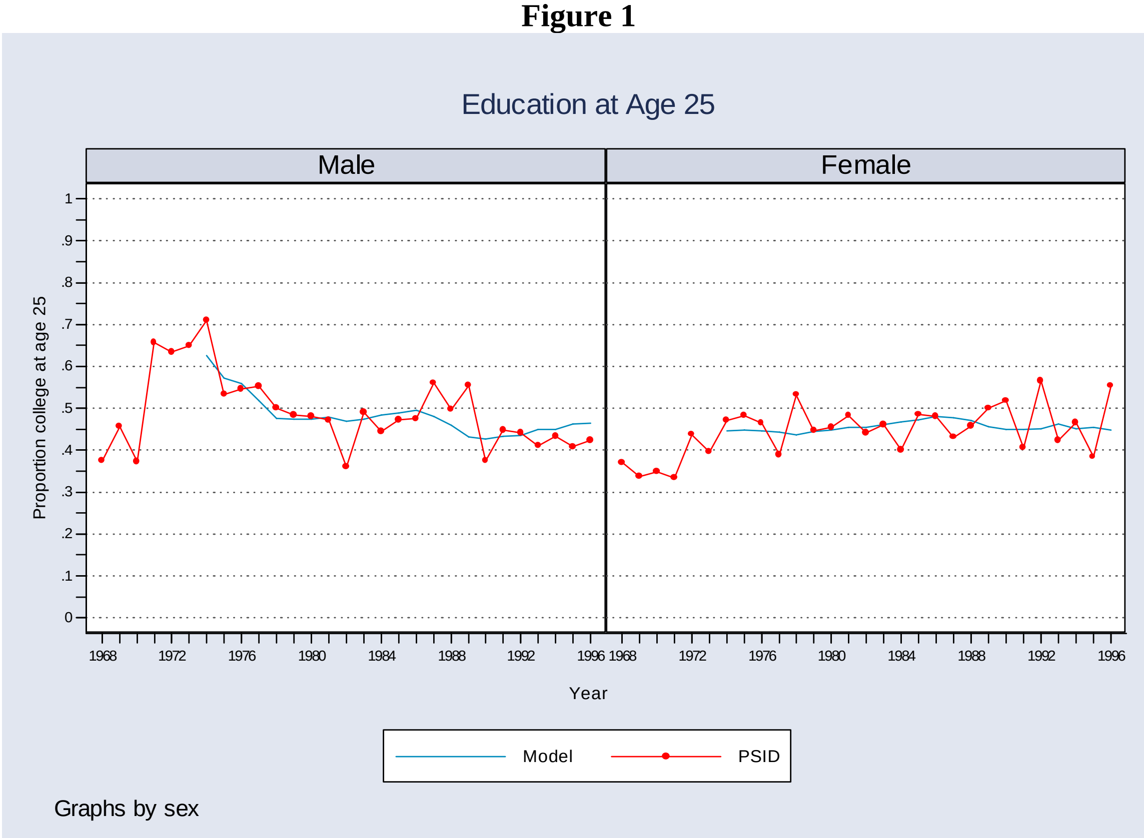


Figure 2

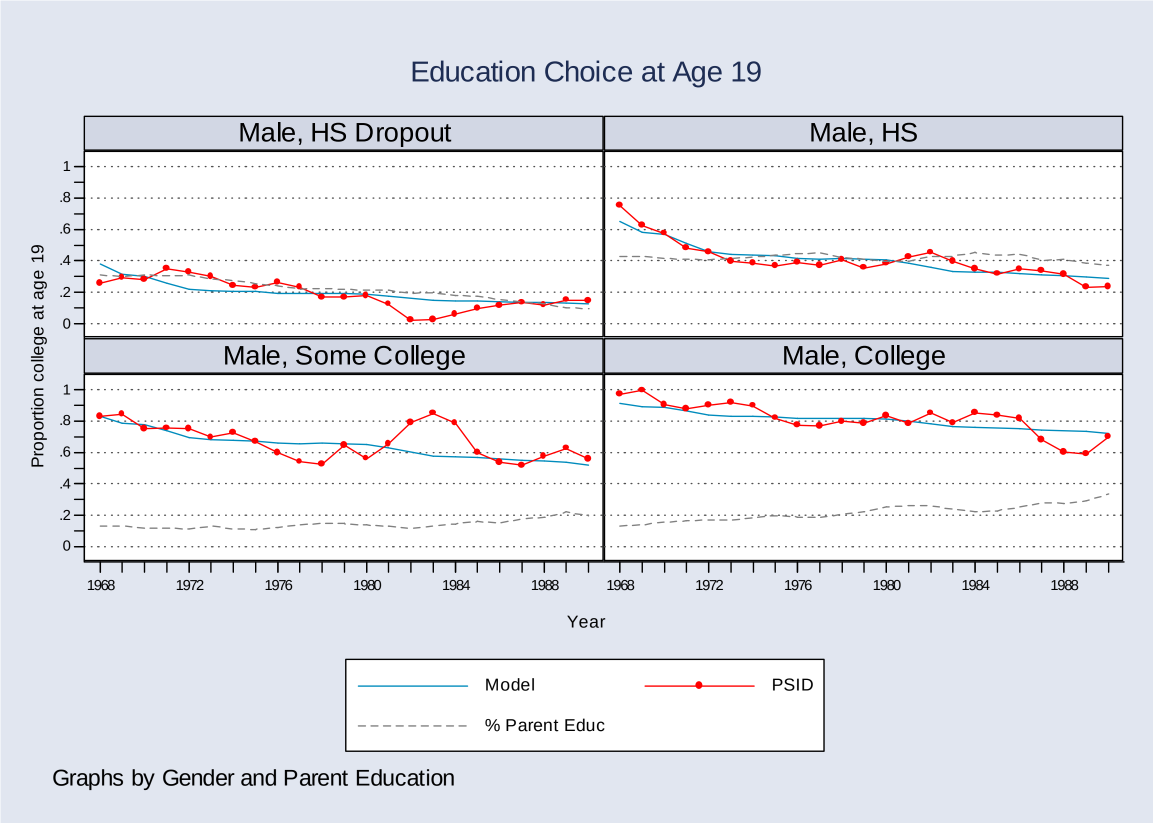
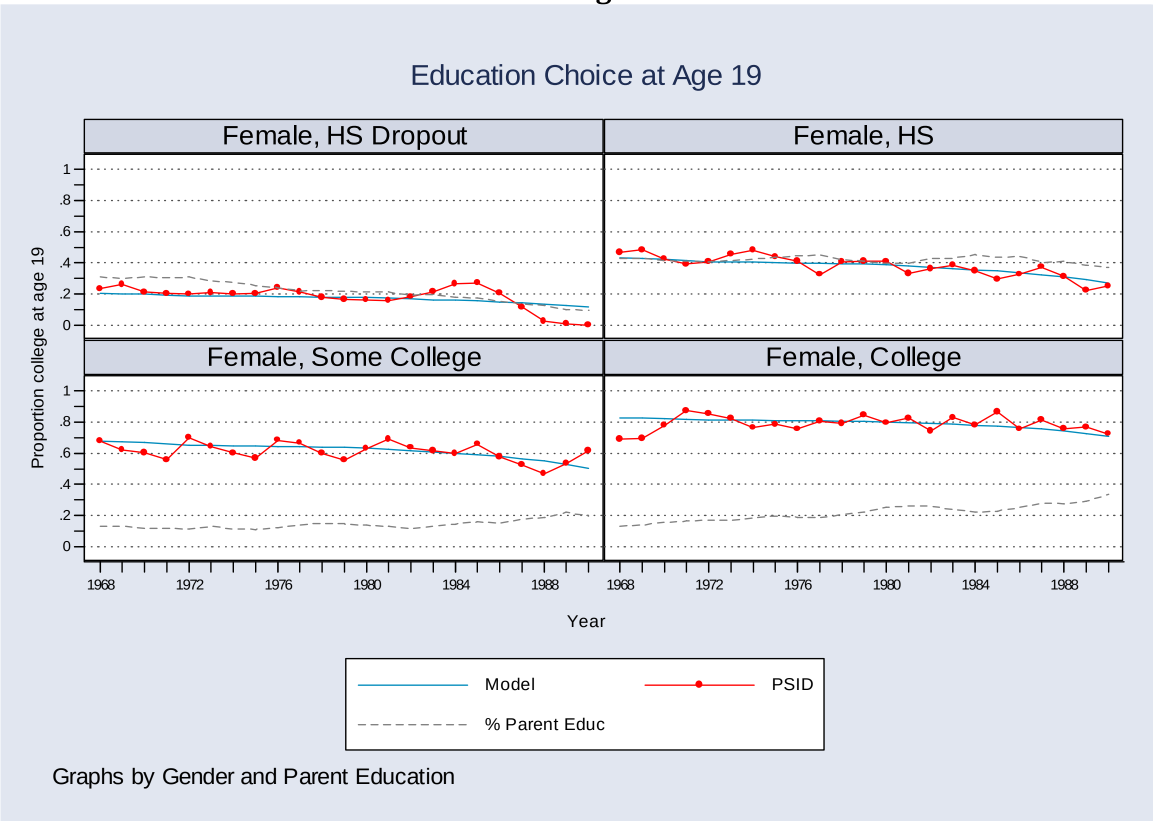


Figure 3



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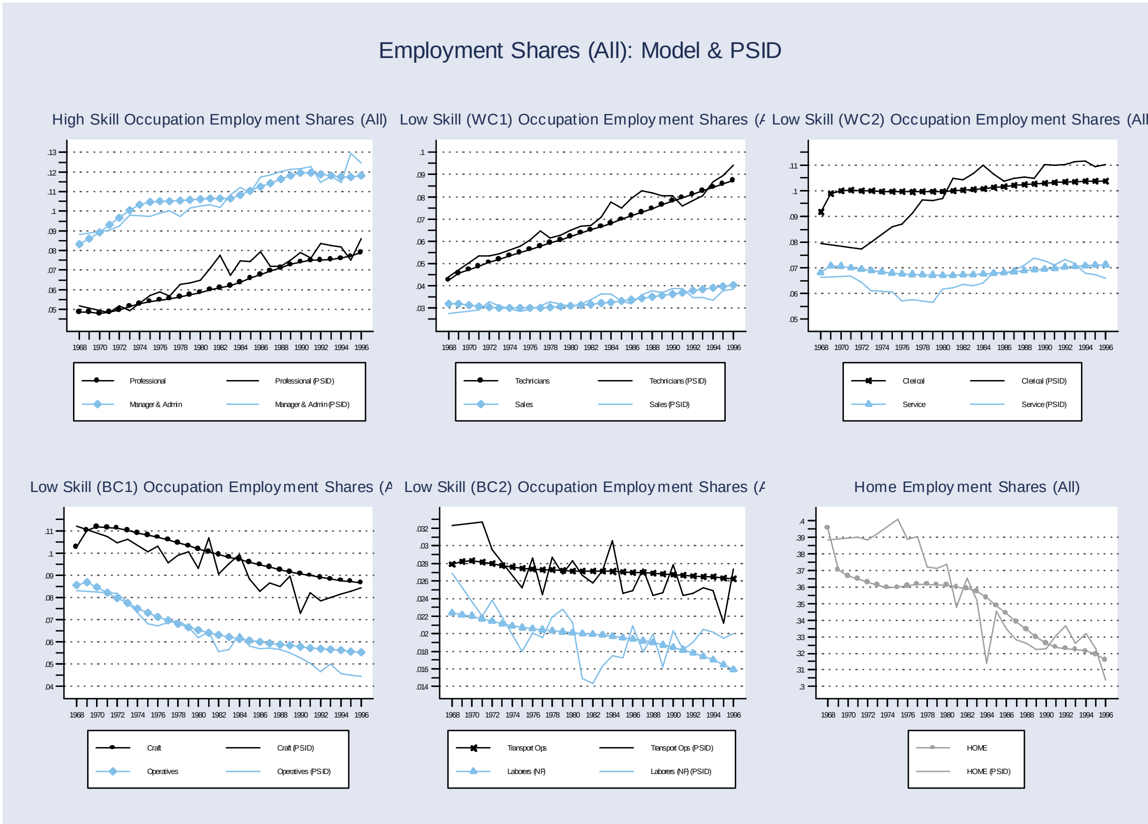
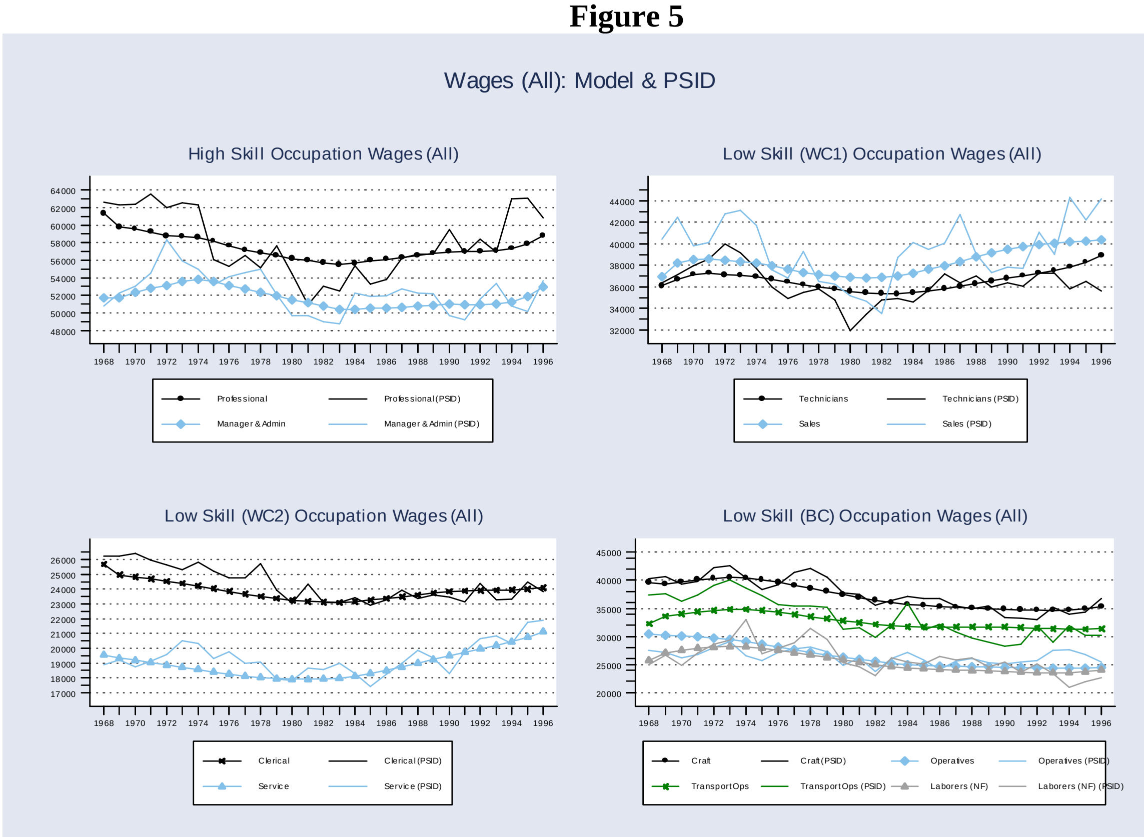


Figure 5



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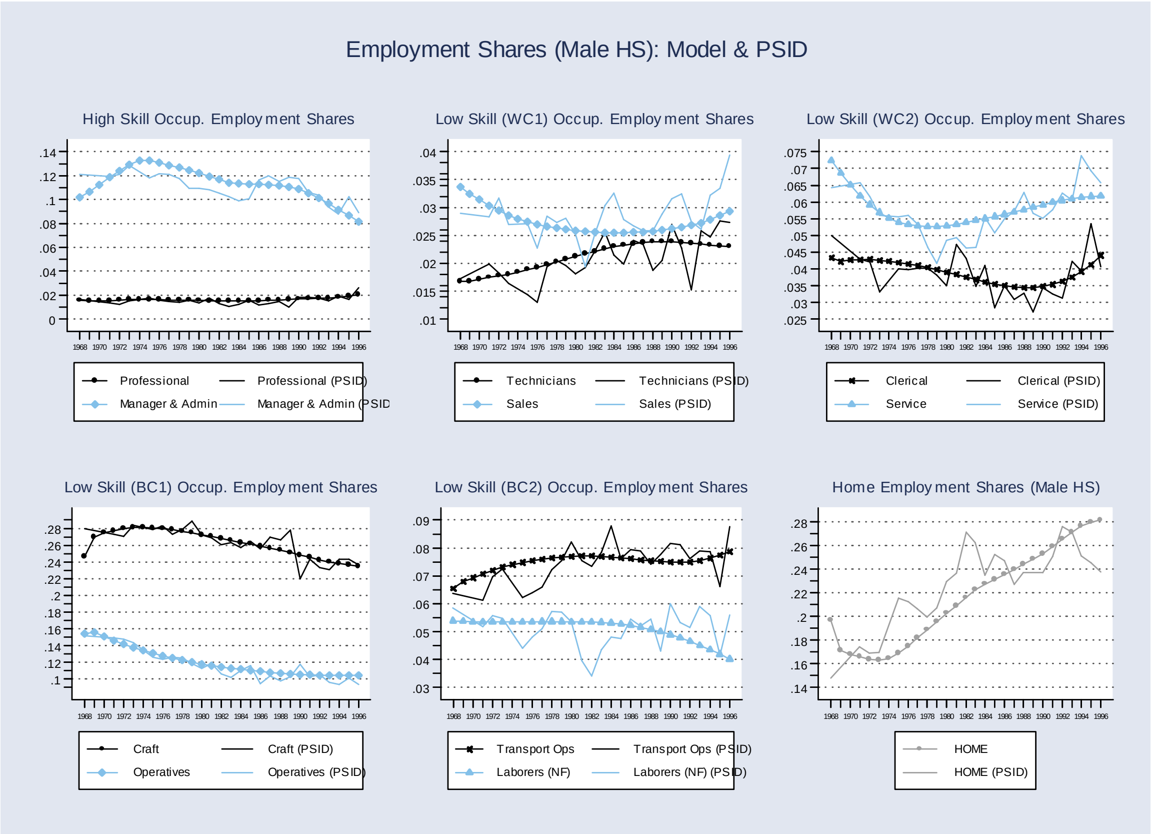

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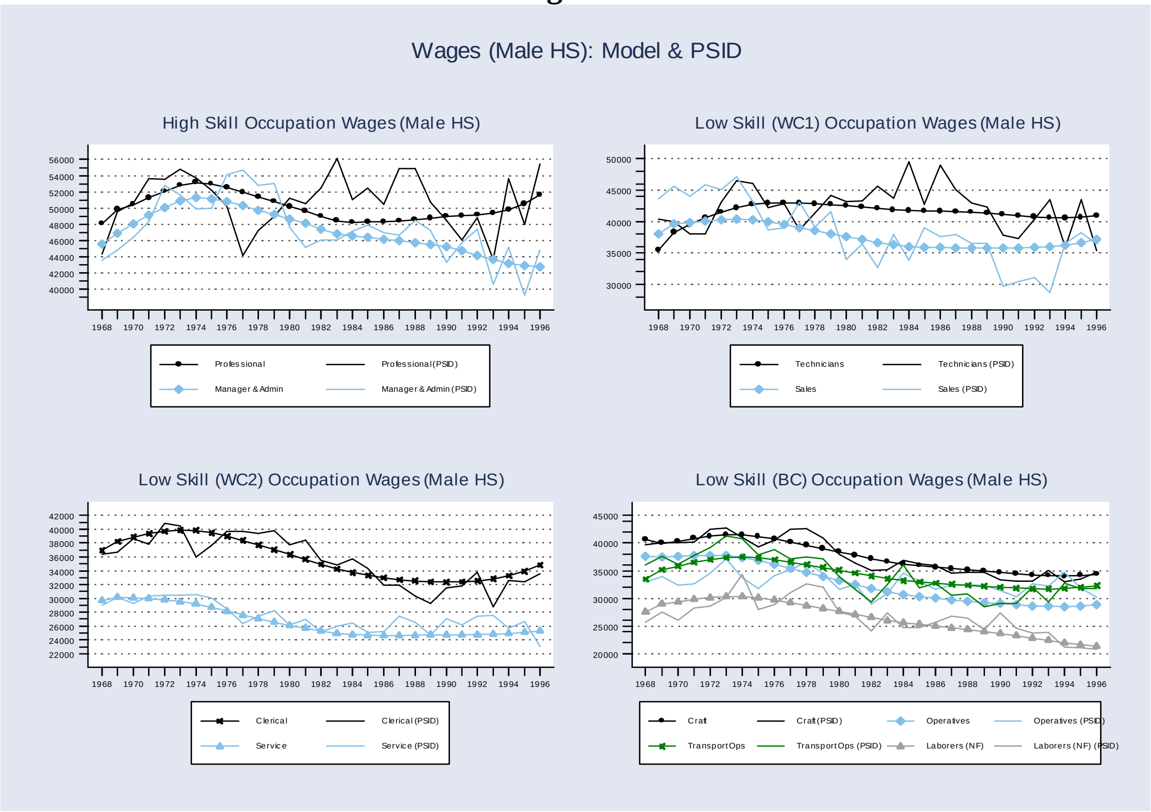

Figure 8

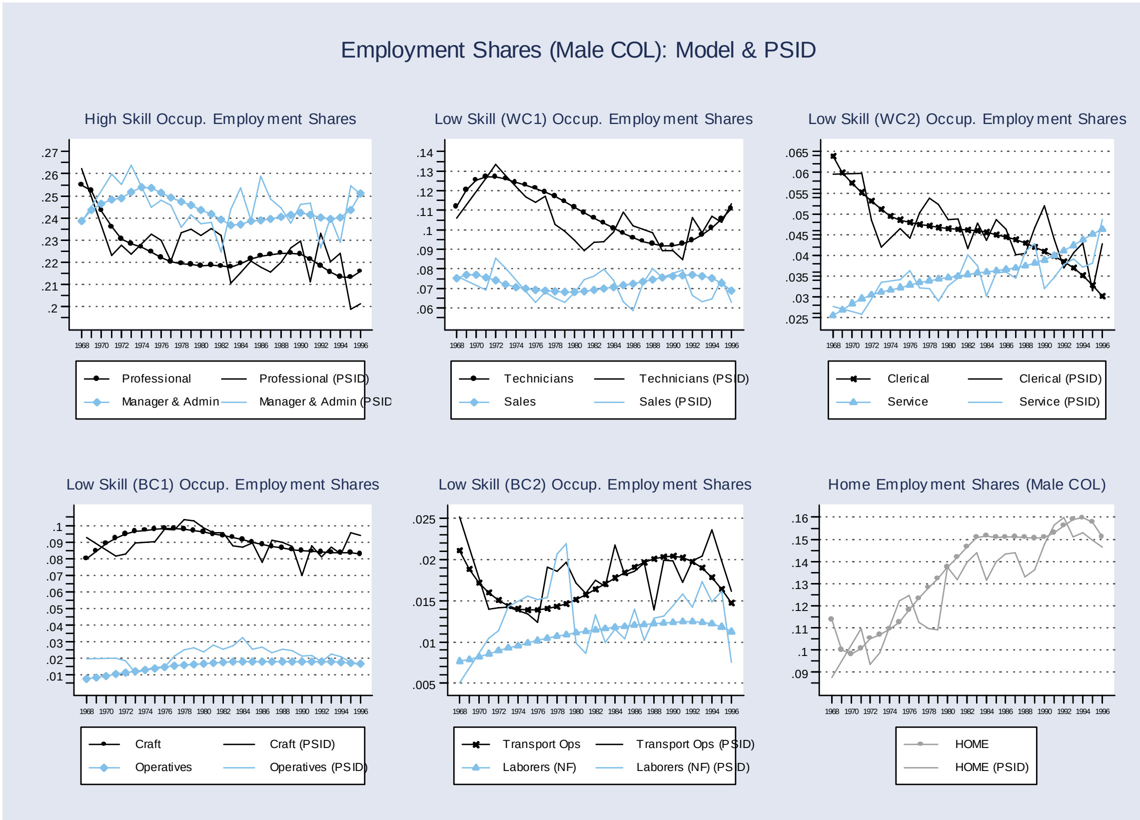

Figure 9

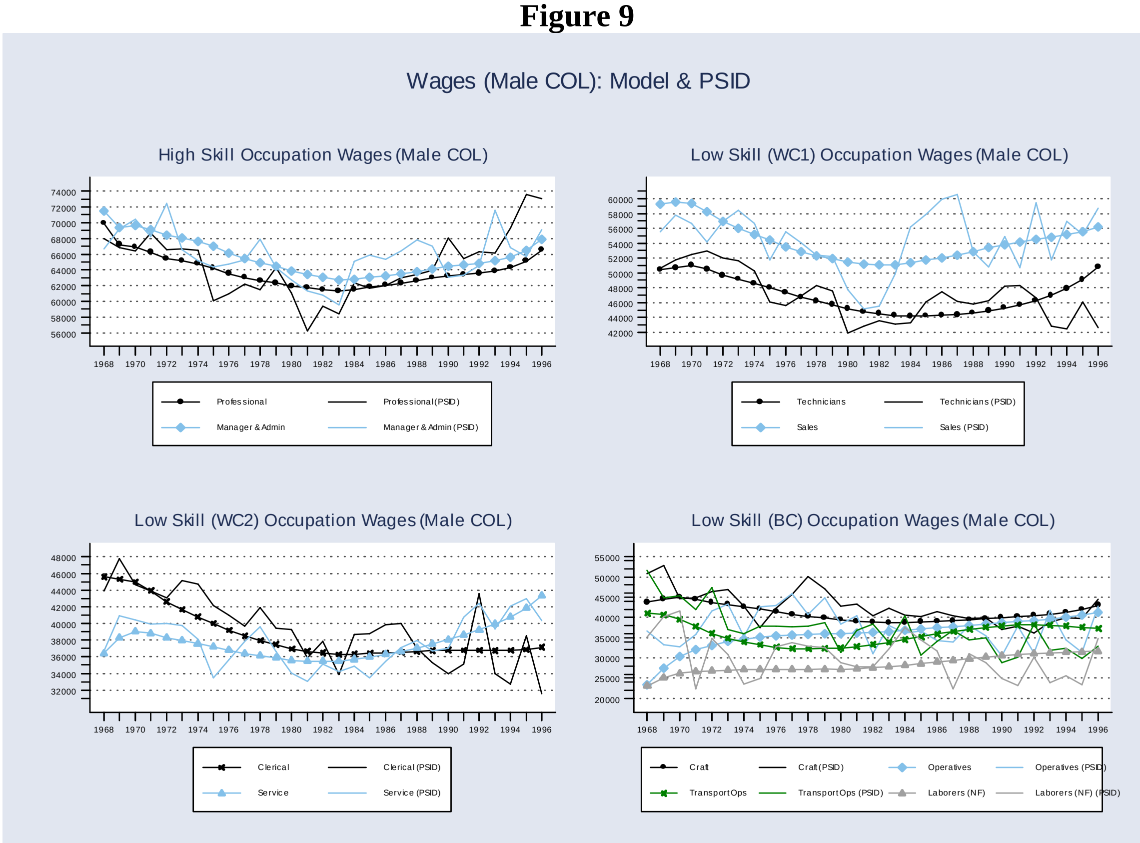

Figure 10

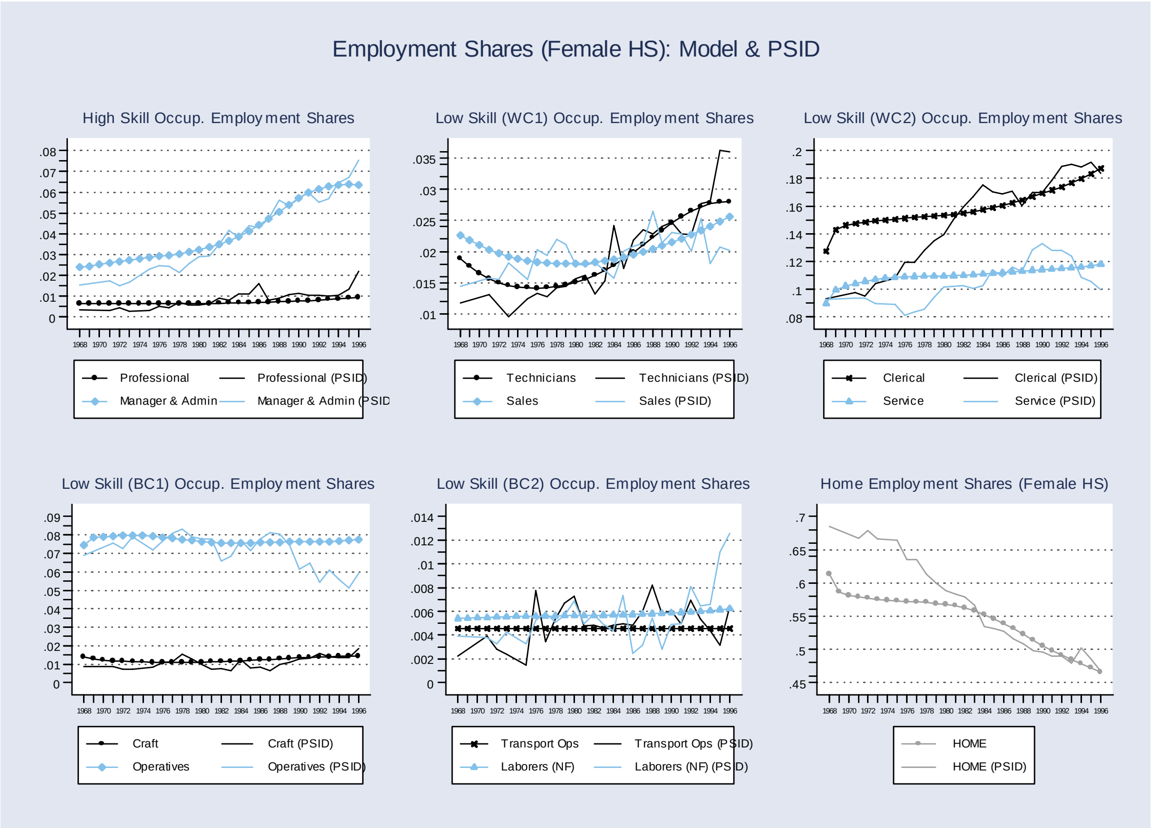

Figure 11

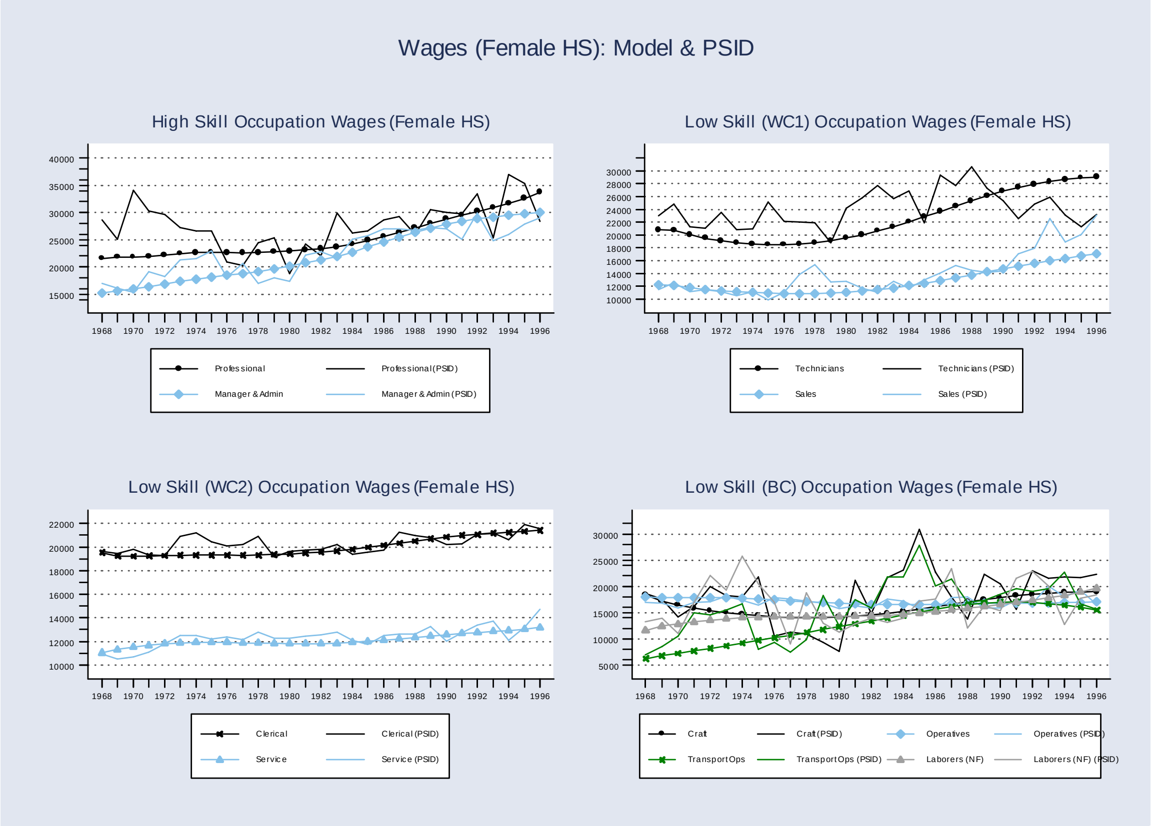

Figure 12

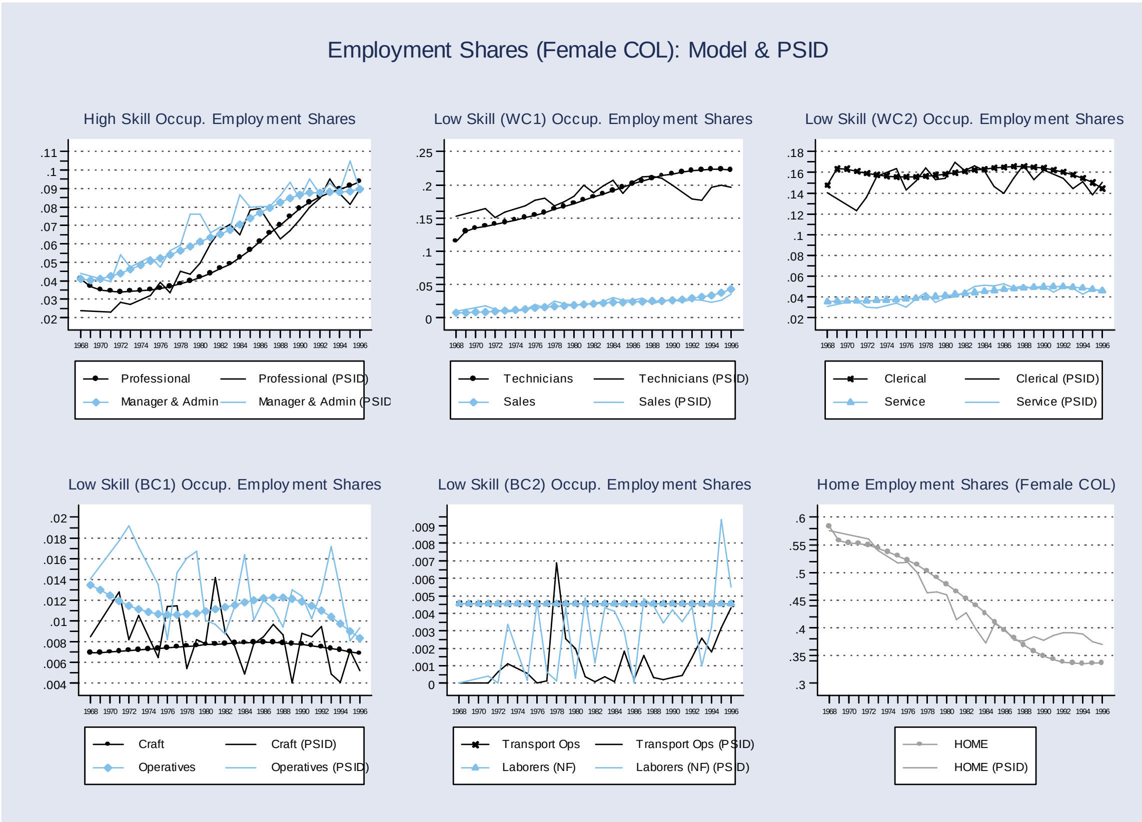

Figure 13

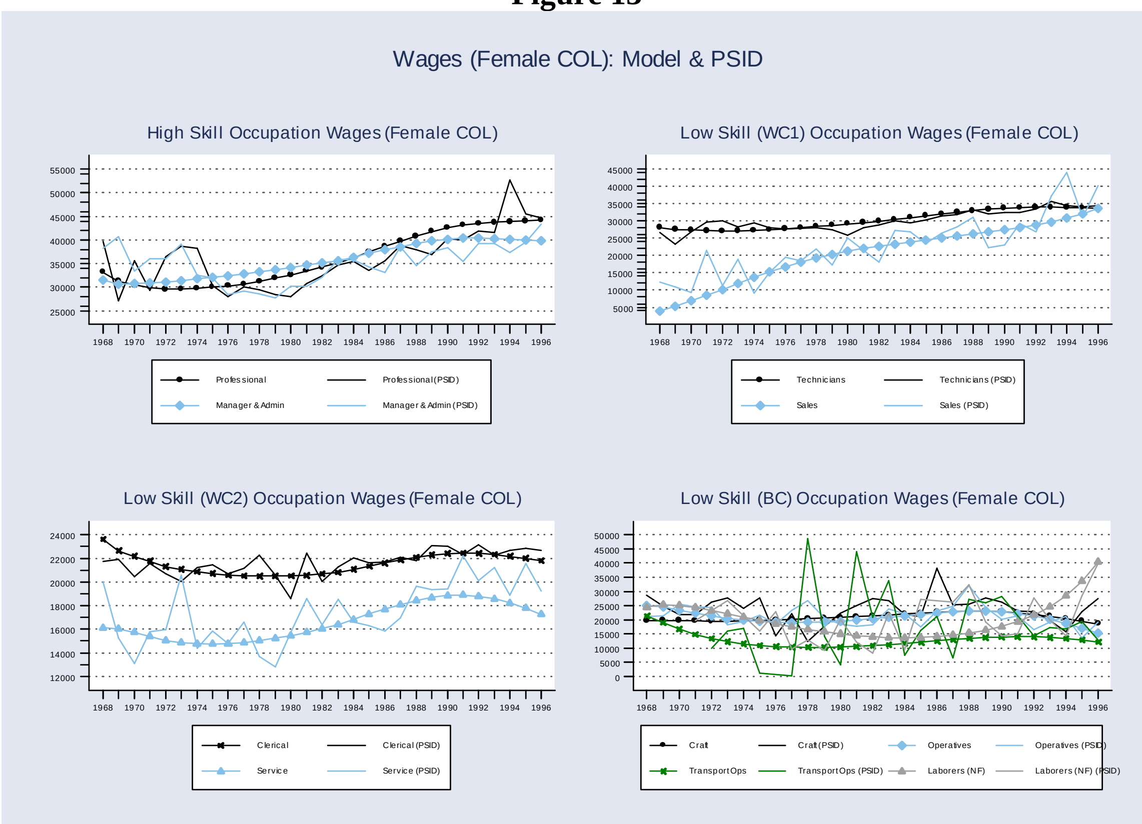

Figure 14

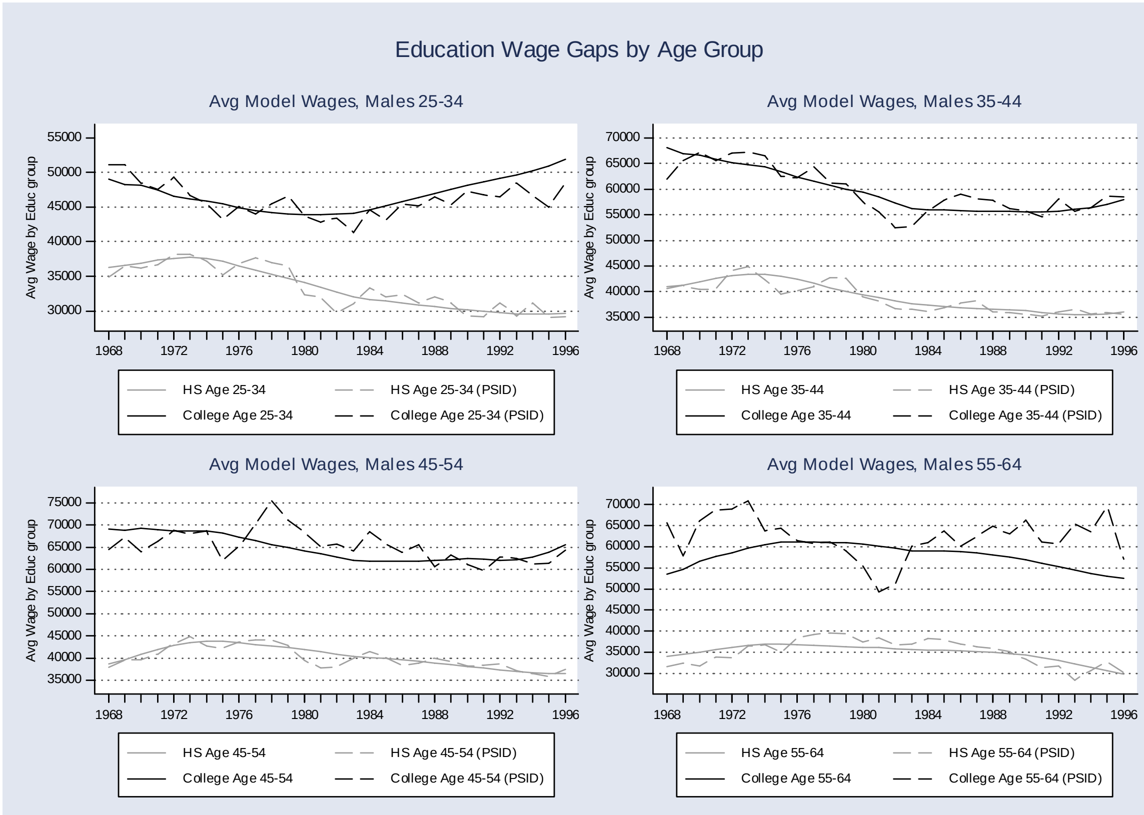

Figure 15

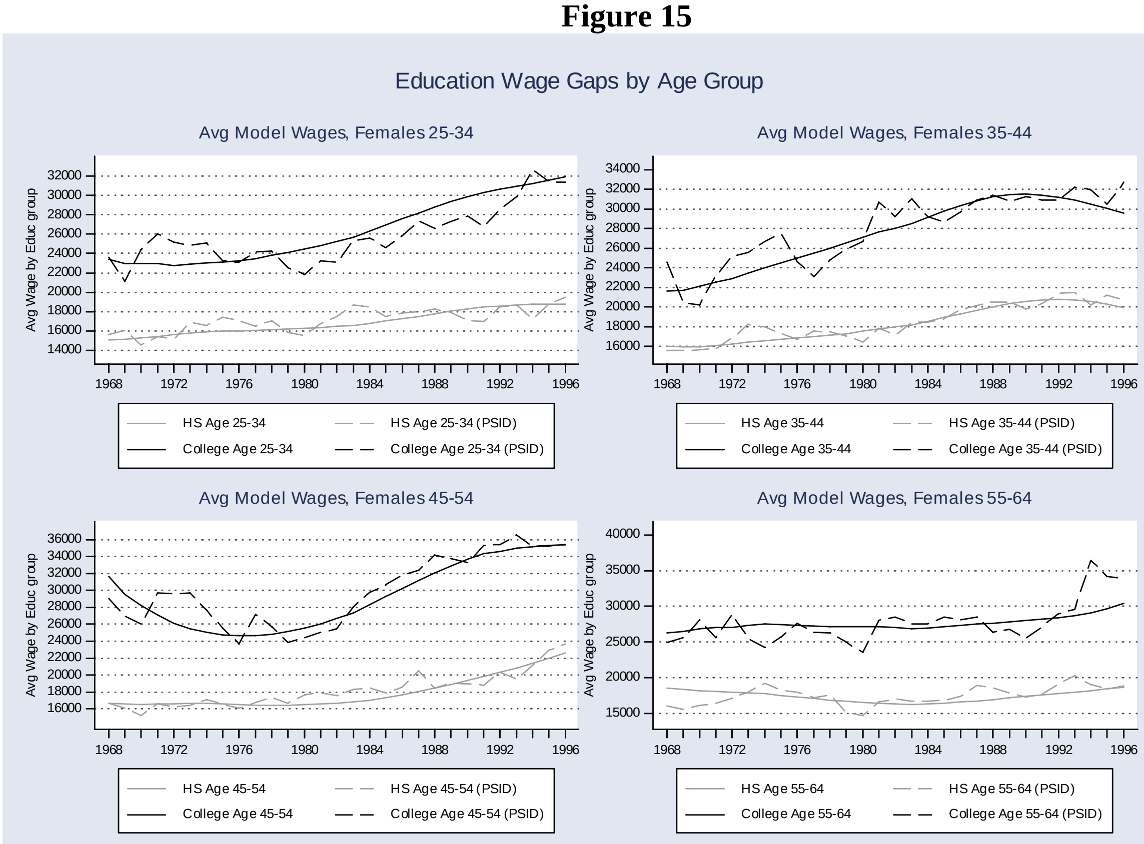

Figure 16

Table 1 – CES Elasticity and TFP Parameters

Parameter Name	*Exogenous Capital Model* Estimate	Std. Error	
ρ_s – capital, skilled labor	-1.12	(0.00)	**
ρ_u – capital+skilled, unskilled	0.69	(0.02)	**
ρ_L – services, blue collar	-0.78	(0.45)	
ρ_H – professionals, managers	0.84	(1.56)	
ρ_{u1} – four service occupations	0.14	(0.86)	
ρ_{u2} – four blue collar occupations	0.04	(0.56)	
ρ_e – high school, college	0.38	(0.47)	
ρ_g – male, female	0.81	(0.27)	**
ρ_a – four age groups	0.90	-------	

Implied Elasticities of Substitution: $\sigma = 1/(1-\rho)$

	Exogenous Capital Model	Endogenous Capital Model	
σ_1 – capital, skilled labor	0.47	0.41	
σ_u – capital+skilled, unskilled	3.23	1.75	
σ_L – services, blue collar	0.56	0.34	
σ_H – professionals, managers	6.25	9.09	
σ_{u1} – four service occupations	1.16	1.41	
σ_{u2} – four blue collar occupations	1.04	1.25	
σ_e – high school, college	1.61	1.59	
σ_g – male, female	5.26	4.76	
σ_a – four age groups	10.00	10.00	
Scale and Neutral Technical Progress			
$b(0)$	14.8	.0787	**
$b(1)$	.0038	.0019	**

Table 2- Simulated Elasticities

Groups	*Elasticity Estimates* *Exogenous Capital Model* min	max	*Endogenous Capital Model* min	max
HS, College	1.15	1.26	1.18	1.30
Male, Female	1.85	2.20	2.02	2.20
Skilled, Unskilled Occupations	0.72	1.09	1.09	1.26

Table 3 – Occupational Choice

Parameter Name	Estimate	Std. Error	
A. Values of Occupations			
Annual Earnings – α_1	8.62E-05	(2.67E-05)	*
Education difference – α_2	1.24	(0.49)	*
Lagged Occupational Choice Probability – α_3	1.41	(0.42)	*

Non-pecuniary payoffs from occupations, by Gender/Education Group – ($\alpha_{0,g,e,k}$ $g=M,F,\ e=HS,COL,\ k=1,10$)

	Males		Females	
High School Graduates				
(1) Professionals	-1.65	(0.07)*	-1.31	(0.33)*
(2) Managers	0.15	(0.18)	1.01	(0.21)*
(3) Technicians	-0.80	(0.07)*	0.50	(0.35)
(4) Sales	-0.55	(0.02)*	1.04	(0.48)*
(5) Clerical	-0.24	(0.01)*	2.23	(0.25)*
(6) Service	0.84	(0.20)*	2.50	(0.40)*
(7) Craft	1.21		-0.27	
(8) Operatives	0.97	(0.04)*	1.76	(0.24)*
(9) Transport Operatives	0.44	(0.00)*	$-\infty$	
(10) Laborers	0.73	(0.20)*	-2.08	(0.27)*
College Graduates				
(1) Professionals	-0.94	(0.80)	-0.12	(0.27)
(2) Managers	-0.82	(0.78)	0.33	(0.15)*
(3) Technicians	-0.15	(0.43)	1.49	(0.06)*
(4) Sales	-0.95	(0.56)	0.17	(0.10)
(5) Clerical	0.17	(0.06)*	2.62	(0.36)*
(6) Service	0.22	(0.04)*	2.05	(0.53)*
(7) Craft	0.89		-0.77	
(8) Operatives	-0.42	(0.18)*	0.32	(0.52)
(9) Transport Operatives	-0.42	(0.15)*	$-\infty$	
(10) Laborers	-0.46	(0.30)	$-\infty$	

B. Value of Outside Option (Home)			
Constant – α_{h0}	3.29	(0.66)	*
Time Trend – α_{h1}	0.0174	(0.0046)	*
Female Const. Shift – $\alpha_{h0,f}$	2.02	(0.03)	*
Female Trend Shift – $\alpha_{h1,f}$	-0.0283	(0.0048)	*

Age effects on Value of Outside Option (by Gender) – $\alpha_{g,a}$

Age Range	**Males**		**Females**	
25-34	0.00		-0.01	(0.06)
35-44	0.59	(0.29)*	0.00	
45-54	1.28	(0.37)*	0.13	(0.02)*
55-64	1.85	(0.25)*	0.73	(0.03)*

Note: For identification, we normalize (i) the non-pecuniary reward for one occupation for each gender/education group and (ii) the non-pecuniary reward from the outside option for one cell within each age/gender group. Females rarely chose occupation 9, and female college graduates rarely chose occupation 10, so we assume away such choices and set their non-pecuniary values to large negative values.

Table 4 – Educational Choice

Parameter Name	Estimate	Std. Error	
PV of Lifetime Earnings (Males) – ϕ_{1m}	1.34E-05	(3.07E-06)	*
PV of Lifetime Earnings (Females) – ϕ_{1f}	6.41E-06	(1.30E-07)	*
Cost of College, by Parental Background Type (ϕ_{2b}):			
<HS Parents	6.04	(1.96)	*
High School Parents	4.87	(1.95)	*
Some College Parents	3.82	(1.95)	
College Parents	2.90	(1.95)	
Female Intercept Shift – ϕ_3	4.12	(1.38)	*
Calendar Time Effects:			
Female Time Trend – ϕ_4	1.29E-02	(2.47E-02)	
Female Trend Squared – ϕ_5	-6.84E-03	(5.48E-03)	
Male Time Trend – ϕ_6	9.80E-02	(1.23E-01)	
Male Trend Squared – ϕ_7	-3.34E-03	(1.29E-03)	*
Tuition Cost – ϕ_8	3.53E-05	(1.76E-04)	

Note: The "cost of college" (by parental background type) potentially includes both monetary and non-monetary costs, while the tuition cost is just one component of the monetary cost.