Human Capital and the Gender Gap in Wages*

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Abstract

The Ben-Porath (1967) model of human capital accumulation is extended to measure how much of the gender wage gap over the life cycle is due to the fact that working hours are lower for women than for men. The theory incorporates labor supply and fertility decisions into an otherwise standard Ben-Porath model. The human capital technology and the distribution of learning abilities are calibrated using male wage data. The calibration of females assumes that children increase the cost of working full-time and follows an indirect inference approach to estimate the marginal effect of children on labor-participation costs. We find that the theory accounts for all of the increase in the gender wage gap over the life cycle in the NLSY79 data for non-college females and for about two thirds of the increase in the gender wage gap of college females.

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1 Introduction

This paper extends the Ben-Porath (1967) model of human capital accumulation to measure how much of the gender wage gap over the life cycle is due to the fact that working hours are lower for women than for men. We develop a theory that incorporates labor supply and fertility decisions into an otherwise standard Ben-Porath model. Individuals are heterogeneous in learning abilities and decide whether to work part time, full time, or not to work. We assume that there are no gender differences in the human capital technology or in the distribution of learning abilities. We use data on wages of men to calibrate the human capital technology and the distribution of learning abilities, following the approach pioneered by Huggett et al. (2006, 2011). Clearly, a theory of gender differences needs to introduce some differences between males and females. While there are many ways one could introduce gender differences, our approach is to assume that the bearing and presence of children increase the cost of working full-time. The model is calibrated to the fertility patterns of college and non-college women in the data and the calibration uses an indirect inference approach to ensure that the estimated impact of children on the labor supply of mothers in the model economy is consistent with the one estimated in the US panel data. The quantitative theory is then used to measure human capital accumulation of females during the life cycle.

Our investigation is motivated by some observations we document on data from the 1979 National Longitudinal Survey of the Youth (NLSY79). We build detailed labor market histories of men and women and show that men work much more hours than women. Adding up weekly hours of work over the life cycle, we find that by age 40 the gender differences in cumulative hours of work are 45% among non-college individuals and 27% among college individuals. Gender differences in labor supply are acompained by substantial differences in wage growth over the life cycle. Over the first 20 years of labor market experience men's wages grow one percentage point more per year than women's wages. We also document that children have an important role in generating gender differences in labor supply by comparing labor market histories of mothers and non-mothers.

In our extended Ben-Porath framework, fertility decisions interact in non-trivial ways with human capital investment and labor supply decisions. Human capital investments and labor market decisions are jointly determined because human capital is accumulated on the job and because its return depends on future labor supply decisions. Fertility decisions are also jointly determined with the labor supply and investment decisions because children increase the cost of work and may lead to a reduction in expected future hours of work and, hence, in the returns to human capital accumulation. In our life cycle framework, the interdependence across decisions is particularly strong for young females because they make fertility choices during a period in the life cycle when the incentives to work and accumulate human capital are strong.

We find that the age-profile of human capital investments of females is below that of males for all ages. Young females have weaker incentives to invest in human capital than males because their expected lifetime labor supply is lower than that of males. The gender differences in human capital investments grow substantially as females age and give birth to children, reach a peak, and then decrease monotonically and approach zero by age 50. The gender differences in investment patterns in the model economy imply that the gender wage gap rises by about 22 percentage points for non-college individuals between ages 17 to 40 and by about 12.5 percentage points for college individuals between ages 23 to 40. Altogether, the model accounts for all of the increase in the gender wage gap over the life cycle for non-college individuals and for about two thirds of the rise in the gender wage gap for college individuals.

Learning ability matters importantly for the interactions between fertility, labor market, and investment decisions in the calibrated model economy. Females with high learning ability, everything else equal, face higher returns to human capital accumulation than the average ability-person in the population, making them more willing to work long hours in order to accumulate human capital and less likely to give birth and diminish their labor market attachment after becoming mothers. This is illustrated in a counterfactual experiment that simulates the behavior of college women assuming that they exhibit the distribution of learning abilities of non-college females. We find that the fertility rate of college women increases from 1.54 to 2.12. Heterogeneity in learning abilities also matters for the variation in fertility behavior of females within education groups.[1]

In the model economy, the impact of children on their mother's labor supply is also quite heterogeneous across females of different learning abilities. This effect is assessed by partitioning, for each education group, the population of females in a low and a high learning-ability group. Then, we use (for each ability-education group) model simulated data to estimate the probability that employed females work part time conditional on the number of children, a dummy for the presence of children younger than age 6, and a full set of age dummies. We find that the marginal effect of children in the probability of part time employment (conditional on employment) is much larger for the low ability group. In the case of non-college females, the presence of a child aged less than 6 years increases the probability of part time employment (conditional on employment) by 5 percentage points for the low ability group and by 2.7 percentage points for the high ability group. For college females, the presence of a child younger than age 6 increases the probability of part time work (conditional on employment) by 13 percentage points and 3.6 percentage points for college mothers in the low and high ability groups.

The theory predicts that wage growth across females within education groups should be positively correlated with the age at which they become mothers. This prediction is tested in two ways using NLSY79 data. First, for each education group, we compute the average annual wage growth over the life cycle (up to age 40) for each mother in the NLSY data and compute the correlation coefficient between the annual wage growth and the age of mothers at first birth. We find that these two variables are positively correlated in the NLSY79 data, and that this correlation is quantitatively close to the one obtained in the model simulated data. One may suspect that the positive correlation between wage growth and the age of mothers at first birth is just reflecting the fact that women who become mothers at a late age have invested more in human capital than the average women in the population of mothers. While this is consistent with the theory, a stronger test arises by focusing on how wage growth of females before they become mothers correlates with the age of mothers at first birth. The idea is that if learning ability is important for fertility and human capital accumulation decisions,

[1] For instance, while the mean fertility rate at age 40 among non-college women is 1.94 children, the number of children varies from 2.1 to 1.88 as ability increases. The median age at first birth increases by almost two years as ability increases from the lowest to the highest level. Intuitively, high ability women tend to delay the birth of the first child and to bear fewer children in order to minimize the impact of children on their lifetime labor supply and human capital accumulation.

then we should expect that the (annual) average wage growth of mothers -prior to giving birth to their first child -to rise with the age at which women become mothers. We find that this is true in the NLSY79 data, supporting the idea that women who give birth to their first child at a later age are of a higher learning ability as predicted by the theory.

Our paper is motivated by some basic insights from human capital theory as well as by some observations regarding the labor supply of women. The theories developed by Becker (1967) and Ben-Porath (1967) stressed that the incentives to accumulate human capital vary along the life cycle and that they are directly proportional to the time one expects to work over the lifetime. The idea that women may face different incentives to accumulate human capital than men due to a higher relative value of non-market activities can be traced back to the influential work of Mincer and Polacheck (1974).[2] The Ben-Porath (1967) model is a natural candidate for modeling human capital in our study because it is well known, has been the basis for both theoretical and empirical analysis of human capital, and there is a recent literature in macroeconomics that has used the Ben-Porath model to study distributional issues in life-cycle settings.[3] Hence, we can build on insights developed in recent work. In particular, Huggett et al. (2006, 2011) have shown that the Ben-Porath (1967) model can replicate important facts on the US earnings distribution of males. By modeling female workers and studying gender differences in human capital investments, our paper makes a valuable contribution to the Ben-Porath literature.

There is an empirical literature estimating structural models of female participation decisions with endogenous accumulation of experience (Altug and Miller (1998), Eckstein and Wolpin (1989) , Van der Klauuw (1996)). Francesconi (2002) and Keane and Wolpin (2006) model fertility and labor supply decisions jointly and allow for heterogeneity in preferences and uncertainty in wages. As in our paper, dynamics play a role because of expectations and not only through past behavior or past labor market shocks. However, their focus is not on gender differences but on the variation in behavior across women. They find that modeling heterogeneity in preferences is important for fitting the data. While we explicitly model preference heterogeneity across education groups, our model endogenously implies heterogeneity in preferences on fertility and labor supply *within* education groups because of differences in learning abilities. In an exercise that is similar to ours in spirit, Bowlus (1997) estimates a search model to assess the role of gender differences in labor market turnover for understanding the gender wage gap. Our paper is also related to an expanding macroeconomic literature that studies female labor supply and fertility.[4]

There is also an empirical literature studying wage differences between mothers and non-mothers (see for instance Anderson et al. (2002) and Waldfogel (1998)). Empirical studies in this literature emphasize the importance of children on work interruptions of women through destruction of firm-specific skills and good quality job matches. Erosa et al. (2002, 2010) argue that these features can account for only about 10 to 20% of the family gap in wages (wage ratio between mothers and non-mothers). Differently than the large wage losses associated

[2]Gronau (1988) and Weiss and Gronau (1981) are also important early contributions studying how labor market interruptions affect women's investment in human capital.

[3]See, for instance, Heckman et al. (1998), Andolfatto et al. (2000), Guvenen and Kuruscu (2009), Guvenen et al. (2009), Huggett et al. (2006, 2011).

[4]Attanasio et al. (2008), Cardia and Gomme (2009), Domeij and Klein (2010), Greenwood and Guner (2008), Guner et al. (2011), Jones et al. (2011), Knowles (2007, 2009), and Olivetti (2006)

with layoffs, the negative impact of career interruptions due to childbirth on wages is limited by the endogeneity of career-interruption decisions. Instead, in our model the family gap in wages arises because children generate career interruptions at a stage of the life cycle when substantial investment in human capital occurs.

The paper is organized as follows. In the next section we discuss the main features of the NLSY79 data for men and women. In section 3, we describe the economic environment and in section 4, we discuss the calibration. In sections 5 and 6, we present the main quantitative results and in the last section we conclude.

2 Data

We use a panel data from the National Longitudinal Survey of Youth (NLSY79) to document observations characterizing the behavior of a recent cohort of young men and women in the labor market. We emphasize three observations from these data. First, gender differences in wages grow substantially over the life cycle. Second, on average men work much more over the early part of the life cycle than women. Third, the origin of the gender differences in labor supply can be traced to the impact of children in labor market decisions of women. In what follows we document these observations in detail.

Description of the Data The NLSY79 is a panel data of a cohort of individuals that in 1979, the time of the first interview, were between 14 and 21 years of age. By the year 2002, people in our sample are between 37 to 44 years of age and therefore have rich histories of fertility and employment that are the focus of our analysis. In particular, the NLSY79 documents labor market histories of people for every week in the sample, allowing us to study the impact of children on labor market decisions of women. We divide our sample in two educational groups and we refer to them as non-college and college. We define college individuals as those who attain 16 years of education or more and we exclude from the sample individuals with more than 20 years of education. In our data the fraction of college individuals in the population is the same for men and women and it is about 25%.

Gender Differences in Wages A salient feature of the labor market is that the average hourly wage of women is substantially lower than the average wage of men. In our sample of the NLSY79, the average wage ratio between women and men is 0.78. Although wages grow substantially over the life cycle for both men and women, the gender wage ratio decreases over the life cycle −the gender gap in wages increases with age. The increase in the average wage over the life cycle for men and women for both educational types is shown in Figure 1. Whereas the average wage of non-college individuals increases between age 17 to age 40 by a factor of 2.45 for men, it increases by a factor of 1.95 for women. The gender difference in wage growth for non-college individuals is on average about 1 percentage point per year and accounts for an increase in the gender wage gap between ages 17 to 40 of about 20 percentage points. For people with college education, the average wage between age 23 to age 40 increases by a factor of 2.28 and 1.77 for men and women, respectively. These observations imply a gender difference in wage growth of 1.3 percentage points per year and an increase in the gender gap between ages 23 to 40 of 20 percentage points. Altogether, the fact that men more than double their wages in a 20 year period suggests that there are important human capital investments over the life-cycle. Human capital theory suggests that the returns to human capital investments depend on how much hours people expect to work in the future. If men and women differ with respect to their actual or expected attachment to the labor market, their incentives to invest in human capital would differ as well. Hence, human capital theory suggests that it is important to evaluate the extent of gender differences in labor supply in the data.

Employment and Hours On average non-college men work 46% more hours than non-college women (36.2 vs. 24.7 hours per person per week). About 50% of this gender difference in hours of work is accounted for by the gender difference in hours per-worker (intensive margin) while the remaining part is accounted for by the gender difference in the employment to population ratio (extensive margin).[5] We also find substantial gender differences in labor supply among college individuals. College men work 33% more hours than college women, with gender difference in hours per worker accounting for 60% of the total difference in hours of work.

Figures 2 and 3 document the life-cycle path of average hours per-worker and the employment to population ratio for men and women for both educational types. Among non-college, hours per worker and the employment to population ratio increase with age for both men and women, but employment is more prevalent for men than for women at every age group. While the employment to population ratio is about 7 percentage points higher for men than for women at age 17, by age 40 this difference is 13 percentage points. There is also a substantial gap in hours of work among people working: At age 17, employed men spend 4 hours more working per week than women. At age 40 the difference in hours of work is 9 hours per week. Similarly, we find that the gender differences in hours worked and employment rate expand over the life-cycle for college educated individuals. Interestingly, we find that the employment rate and hours per worker of college educated women decrease with age during the child-rearing period.

Children and Labor Market Outcomes Labor supply differences across gender are substantial. What is striking in comparing labor market outcomes of men and women is the role that children play in labor supply decisions of women. We compare statistics for the average of all women and for the average of women who never had children.[6] For the non-college type, the employment to population ratio of women with no children is almost identical to that of men during the life cycle as documented in Figure 2. The pattern of average hours per worker

[5]Hours per person can be decomposed into hours per worker and the employment to population ratio:

$$\frac{H}{P} = \frac{H}{W} \cdot \frac{W}{P} + 0 \cdot \left(1 - \frac{W}{P}\right),$$

where H is aggregate labor hours, P is working-age population, and W is number of people employed. On average, men work 40% more hours than women, while among those working, men work almost 20% more hours than women.

[6]For the last observation of every woman in our sample − when they are between 37 to 44 years of age − we consider women who had not had children up to that point and we refer to them as women with no children (Women NoKever in the graphs).

is also similar between non-college men and women with no children except for a constant gap (roughly 5 hours per worker per week or about 10% of the hours per worker of males) (see Figure 3). Among the college educated, we also observe that women with no children work more often and more hours than the average women.[7]

The fact that there is a negative association between children and female labor supply in the data, does not necessarily imply that children have a negative effect on female labor supply as this empirical relationship could well be due to selection: Women can be heterogeneous in their labor market attachment and mothers could be drawn from workers with low preferences for work. To address this concern, we discuss data suggesting that children have a negative impact on female labor supply. A first clue of the role of children is in Figure 2: Gender differences in labor supply grow substantially at the ages when women start bearing children. While for non-college individuals the gender differences in employment rates grow substantially after age 23 and start diminishing rapidly before age 30, for college individuals the employment rate only differs across genders after age 26 and these differences are still substantial by age 40. These patterns are consistent with the fact that college educated women tend to give birth at older ages than less educated females and with the view that children -of young age- negatively affect the labor supply of mothers. The employment rates between mothers and non-mothers differ substantially, particularly when children are young. While women with no children have an average employment to population ratio similar to the average of men (81% vs. 82% for non-college and 86% vs. 90% for college), women with at least one child under 6 years of age have employment to population ratios below 60% in the case of non-college women and below 73% in the case of college women. The employment ratio of women with young children (less than a year old) is lower than 45% in the case of non-college and 62% in the case of college. The fact that the employment rate of mothers grow substantially with the age of their youngest child, suggests that the low employment rate of mothers is not due to permanent differences in the labor market attachment between mothers and non-mothers.

More direct evidence on the importance of children in generating gender differences in labor supply can be obtained by exploiting the panel dimension of our NLSY data. First, we show that the duration of non-employment spells differs substantially across genders and that children play a crucial role in accounting for these observations. We divide all non-employment spells of women between spells that involve the birth of one child at the time or during the job separation (we call these spells "birth") and spells that do not involve the birth of a child ("No birth").[8] An important fraction of all non-employment spells do not involve the birth of a child (almost 82%) and the average duration of these spells is similar to that of men (46 weeks for men vs. 50 weeks for women in the case of non-college and 42 weeks for men vs. 38 weeks for women in the case of college). Table 1 documents that the main difference in

[7] Interestingly, while non-college women with no children work as often as men, the employment rate of college women with no children is lower than the one of men (see Figure 2). A possible explanation for the different behavior of women with no children across educational types is that college women marry wealthier men than non-college women.

[8] The NLSY79 provides the necessary information to characterize labor market decisions of women around the birth of a child (6 weeks or less either before or after birth). We restrict our sample to include histories of people that at the start of any spell are 20 years of age or older and we abstract from spells of short duration (6 weeks or less). Childbirth refers to non-employment spells that involve the birth of a child at the start or during the spell. About 82% of all non-employment spells involve "no childbirth" for women, 15% involve the birth of one child and 3% involve the birth of two or more children.

the duration of non-employment spells between men and women is in the spells of women that involve the birth of a child (46 weeks for men vs. 113 weeks for women in the case of non-college group and 42 weeks for men vs. 102 weeks for women in the case of the college category). As documented below, the gender differences in the duration of non-employment spells translate into important differences in accumulated labor market experience.

Second, to document that children have a direct causal effect on female labor supply, we examine labor market decisions of mothers before and after childbirth for all birth episodes in the NLSY. Figure 4 shows that the employment rate decreases during pregnancy and that it slowly recovers after childbirth. For both education groups, the employment rate one year after birth is still more than 10 percentage points below its level prior to pregnancy.

The Accumulation of Experience Women are characterized by lower employment, fewer hours of work, and longer duration of non-employment spells than men. These gender differences in labor supply imply that on average, women accumulate less experience in the labor market than men. Table 2 documents the average accumulated experience for men and women at age 40 in our panel data, for two measures of experience: Accumulated weeks of work and accumulated weekly hours of work.[9] Table 2 indicates that by age 40, non-college men have accumulated 22% more weeks of experience than non-college women, and 45% more hours of work than non-college women. The gender differences in labor market experience are lower but still substantial for the college type. (see Table 2). Women with children accumulate much less experience (measured in hours) than men, 53% less in the case of non-college women and 33% less in the case of college women. We emphasize that the gender differences in experience that we obtain by adding up hours of work over the life-cycle in Table 2 are much larger than the ones implied by commonly used measures of experience such as potential experience (age-years of schooling-6) or actual experience (accumulated years of employment). We conclude that the large gender differences in cumulative hours of work, suggest that women face much lower incentives to accumulate human capital than men.

3 Economic Environment

We consider a life-cycle economy populated by male and female individuals. The model period is set to a quarter. In each period people make labor supply and human capital investment decisions. Females also make fertility decisions. We assume that the population is divided in two (exogenous) education groups representing college and non-college individuals. While many of the parameters and shocks are assumed to vary across education types, we do not index parameters and variables with an education index to keep the notation as simple as possible. To keep our analysis simple, we abstract from marriage, inter-temporal consumption smoothing, and general equilibrium interactions.[10] Below we present the key ingredients of

[9]There are some cases of people that are employed but report either zero hours or there are no hours reported. The numbers presented in Table 2 assume these cases as zero hours, but alternative assumptions yield similar results.

[10]Our theory can accommodate marriage by assuming that matching in the marriage market is independent of fertility, labor market, and human capital decisions. Extending the theory to model a non-trivial joint decisions by husbands and wives is a daunting task since we would need to model three endogenous state

our framework.

Life-Cycle We assume that individuals of the two education types retire from the labor market at age 65. Modeling a finite lifetime allows us to capture the life-cycle aspect of fertility and human capital accumulation decisions. Moreover, the model generates life-cycle observations for employment and wages that can be compared with data.

Labor Decision Each period (quarter) people decide whether to work full time (n_f), part time (n_p), or not at all (n=0). Labor earnings enter linearly in the utility function but working entails a fixed cost of work. This trade-off also has a dynamic component since human capital is only accumulated while working. We interpret the cost of work as capturing the disutility cost of working but also explicit and implicit costs of work, such as the lost value in home production, commuting costs, and the extra expenses in food consumption due to labor market participation. The cost of work is assumed to depend on the amount of hours worked (part time vs. full time), a shock to the cost of participating in the labor market, and individuals' characteristics (human capital, age, gender, education, and, in the case of females, total number of children and number of children younger than age 6). The participation-cost function will be calibrated so that the model reproduces the life-cycle employment rates. The stochastic shock to the cost of participation κ is introduced so that the model is consistent with data on the duration of non-employment spells. For females, the impact of children on the fixed cost of work will be estimated using an indirect inference approach.

Human Capital Accumulation Decision We model human capital accumulation on the job in the Ben-Porath tradition. An individual's human capital at age $j+1$ is an increasing function of an idiosyncratic shock z_{j+1}, current human capital h_j, time devoted to human capital investment n_i, and learning ability a:

$$h_{j+1} = exp(z_{j+1})H(a, n_i, h_j) \tag{1}$$

Individuals are born with an initial human capital (h_0) and a learning ability (a) which is fixed over the individual's lifetime. The initial value of human capital and the learning ability (a) are drawn from a bivariate lognormal distribution. Heterogeneity in learning ability will produce mean human capital and wage profiles with different slopes across individuals. We follow Huggett et al. (2011) in modeling a shock to human capital (z) drawn from an iid normal distribution across age and individuals. The shock to human capital is introduced so that the rise in the variation in wages over the life cycle is not all due to heterogeneity in human capital investment decisions. That is, part of the heterogeneity in wages is due to human capital being repeatedly hit by shocks.

The wage rate of an individual with human capital h, working n hours, and devoting n_i hours to accumulate human capital on the job satisfies

$$\text{hourly wage} = \frac{h(n - n_i)}{n}. \tag{2}$$

variables (asset accumulation and human capital of husbands and wives) together with discrete (non-convex) labor-participation and fertility decisions.

Note that the Ben Porath model does not model the demand side of the job market so that, in principle, individuals could use all their available working time to accumulate human capital. Following Guvenen and Kuruscu (2009) and Guvenen et al. (2009) we assume that individuals can at most devote a fraction χ of working time n to accumulate human capital ($n_i \leq \chi n$). This constraint implies that individuals can only accumulate human capital if they work ($n > 0$). Moreover, note that an upper bound lower than 100% on-the-job-investments could be the result of fixed cost of work incurred by the firm or minimum wage laws. Such an upper bound is also important for well defined notion of employment in our model economy. Otherwise, some employed individuals in the model economy would accumulate human capital for almost 100% of their working time and earn wages close to zero. Since our calibration will target the evolution of the variance of log-wages over the life-cycle, note that having even a small number of individuals with wages close to zero can distort our quantitative assessment importantly. Following Guvenen and Kuruscu (2009) and Guvenen et al. (2009) we will set $\chi = 0.5$ so that individuals can only devote half of the working time to human capital accumulation.

Fertility Decision We assume that females derive utility from children and from spending time with them at home after giving birth. Moreover, children affect the cost of participating in the labor market and birth episodes may be associated with career interruptions. Therefore, children can have a negative impact on the employment decision of females. We assume that females need a fertility opportunity in order to consider the decision of having a newborn child. Fertility opportunities arise stochastically over time and their likelihood varies with age and the number of children. We introduce fertility opportunities in the model in order to capture time frictions such as finding a partner and biological constraints. Moreover, this assumption allows our model to generate a reasonable age-profile of fertility for each education group.

3.1 The problem of males

We first present the problem of males because it is simpler than the one of females, given that the former do not make fertility decisions. We formulate the decision problem in the language of dynamic programing. The value $V_{j,a}(h,\kappa)$ gives the maximum present value of earnings (net of participation costs) at age j of an individual with human capital h, learning ability a, and the shock to the cost of labor market participation κ.

$$\begin{aligned} V_{j,a}(h,\kappa) &= \max_{n,n_i \leq \chi n} \{-k_m(j,n,h,\kappa) + wh(n-n_i) + \beta E[V_{j+1,a}(h',\kappa')]\} \\ & \quad h' = exp(z')H(a,n_i,h), \\ & \quad n \in \{0, n_p, n_f\}, \end{aligned}$$

where $k_m(j,n,h,\kappa)$ is a function giving the cost of a male working n hours, which depends on his age (j), human capital (h), and stochastic shock κ.

3.2 The problem of females

For ease of exposition, it is convenient to assume that females make fertility decisions prior to the labor market and human capital accumulation decisions (rather than making all decisions jointly). A female starts the period with a state that includes the same variables as men (age j, ability a, human capital h, participation cost κ) plus three additional variables given by the number of children (N), number of children less than six years of age (N_6), value of staying at home with children (v), and a variable (d for domestic status) indicating whether the female is in a non-employment spell originated after giving child birth. The first two additional states variables – number of children (N) and number of children younger than age 6 (N_6) – affect the cost of participating in the labor market, both for part time and full time participation. For ease of computation, we assume that children age stochastically so that the age-distribution of children is described with two discrete state variables (N and N_6). Under this assumption the number of children who become older than age 6 in a given period follows a binomial distribution, as shown in Da Rocha and Fuster (2006). We assume that at the beginning of each period women draw from an exogenous (continuous) distribution a utility value v of spending time with their children. This value is drawn prior to the fertility decision and it can only be enjoyed if the female is in a non-employment spell initiated after giving birth. This is ensure by modeling a state variable d which is set to 1 when the female gives birth to a new child, and it is reset to zero if the woman works. As a result, Since women can only enjoy the utility value of v if d=1, working women cannot quit their job to enjoy the value of v unless they give birth to a child.

After the period starts, there is a fertility stage in which the female faces a fertility opportunity with probability $\theta(N, j)$, which depends on her age and number of children (and education category). Her value function, prior to the realization of the fertility opportunity, is represented by $B_{j,a}(h, \kappa, N, N_6, v, d)$ and satisfies,

$$B_{j,a}(h, \kappa, N, N_6, v, d) = \theta(j, N) \max \{V_{j,a}(h, \kappa, N+1, N_6+1, v, 1), V_{j,a}(h, \kappa, N, N_6, v, d)\} + (1-\theta(j, N))V_{j,a}(h, \kappa, N, N_6, v, d),$$

where the max operator represents the fertility decision and $V_{j,a}$ denotes the value function of a female after the fertility stage. Note that when a female gives birth, the variable d is set to 1 indicating that the female can enjoy the value of staying at home with children v if she does not work.

The labor market decision is represented as follows:

$$\begin{aligned} V^{j,a}(h, \kappa, N, N_6, v, d) &= \max_{n, n_i \leq \chi n} -k_f(j, n, h, \kappa, N, N_6) + wh(n - n_i) + vI_{n,d}h + \gamma_n \log(1+N) + \\ &\quad ...\beta E[B_{j+1,a}(h', \kappa', N', N_6', v', d')] \\ &\quad h' = exp(z')H(a, n_i, h), \\ &\quad n \in \{0, n_p, n_f\}, \\ &\quad d' = 0 \text{ if } n \geq 0, \end{aligned}$$

where $I_{n,d}$ is an indicator function that takes the value of 1 when the female decides not to work $n = 0$ and she has not worked after giving birth $d = 1$. If the female works, next period the value of d will be zero ($d' = 0$). As discussed before, this ensures that females can only enjoy the value of staying at home v if they are in a non-employment spell after giving birth. Note that, differently from males, the function determining the participation costs faced by females in the labor market ($k_f(j, n, h, \kappa, N, N_6)$) depends on the total number of children (N) and the number of children younger than age 6 (N_6).

4 Calibration

Our calibration strategy is as follows. For each educational type, we calibrate most of the model's parameters to panel data of men, in particular, we target the employment ratio and hours of work by age, the accumulation of experience, the duration distribution of non-employment spells. Moreover we use wage distribution facts for males over the life cycle to calibrate the parameters of the human capital technology and the parameters of the distribution of initial human capital and learning abilities. Regarding females, we only calibrate to targets that relate to the number of children and to the employment and hours histories of women after childbirth for each education group. We model the decisions of non-college individuals since age 17 since women between age 17 to age 19 account for 20% of all the births among women in this education group. College individuals are modeled since age 20. The mapping between parameter values and targets in the data is multidimensional and we thus solve for parameter values jointly. For expositional reasons, we next describe the role of each parameter on a specific target as if the parameter has a first-order impact in the target. In Table 3 we report the calibrated parameter values for non-college and college individuals.

4.1 Calibration of Males

Some parameters are selected without solving the model. We set the model period to a quarter and $\beta = 0.99$. In a given quarter, individuals can either work part time of full time. We define full time as working 40 hours per week. The hours of part-time work are set to match the average hours worked among men working less that 35 hours per week in the NLSY, which gives a target of 22 hours per week for college men and 24 hours per week for the non-college. Since investment in human capital in our theory is determined by future (life-cycle) labor supply, we emphasize the importance of obtaining reasonable age profile of hours of work and employment.Another set of parameter values are selected to match certain targets in the data by solving the model. We describe this procedure in detail below.

Labor Participation Cost The function determining how the costs of labor market participation vary with age (j), hours of work (n), human capital (h), and shock to labor participation is specified as follows:

$$k_m(j, n, h, \kappa) = k_j \; \kappa \; h \; c_m(n) \text{ for } j = t_0, ..., 65, \text{ and } n \in \{0, n_p, n_f\}. \tag{3}$$

The costs of labor participation increases proportionally with human capital to be consistent with the fact that there are virtually no differences in lifetime labor supply across individuals in the (permanent) wage distribution (see Erosa et al. (2011)). The constants k_j capture the (deterministic) variation in the life-cycle profile of participation costs and are used to generate a plausible age profile of employment. We search for 9 values of k_j in order to match the employment rate of men at 9 selected ages, with the values of k_j for other ages obtained by linear interpolation. The participation cost of no work is set at zero ($c_m(0) = 0$) and the one for full-time work is normalized to 1 ($c_m(n_f) = 1$). The participation cost for part-time work is obtained to match the fraction of men working part time in our NLSY79 sample. We assume that the stochastic component of the participation cost follows a first order autoregressive process

$$\kappa_j = \rho\kappa_{j-1} + \varepsilon_j, \text{ where } \varepsilon \sim N(0, \sigma_\kappa^2).$$

The parameters (ρ, σ_κ) are selected in order to match the duration distribution of non-employment spells and the mean years of job market experience of male workers at age 40.

Human Capital We assume the following production function of human capital:

$$h_{j+1} = exp(z_{j+1}) \left[h_j + a(h_j n_{i,j})^\alpha \right], \text{ where } z_{j+1} \sim N(\mu_z, \sigma_z^2)$$
$$\text{and } x = (h_0, a) \sim LN(\mu_x, \Sigma).$$

Hence, the following parameters need to be pinned down: $(\alpha,\mu_z,\sigma_z,\ \mu_a,\ \mu_{h_0},\ cov(h_0, a))$. The calibration procedure builds on the findings of Huggett et al. (2011). First, using the implication that in the Ben-Porath model human capital investments approach zero late in the life cycle, these authors estimate the stochastic process of the shock to human capital using PSID data on wages of workers aged 55-65 and estimate $\sigma_z = 0.111$ and $\mu_z = -0.029$. We use these estimates, which imply that one standard deviation shock moves wages by about 11% and an (annual) depreciation rate of about 2%.[11] Second, we set the parameter (α) determining the degree to scale in human capital accumulation to 0.70, which is their preferred value and is right in the middle of the empirical estimates reviewed in Huggett et al. (2011). Third, we pin down the value of $(\mu_a,\ \mu_{h_0},\ cov(h_0, a))$ by targeting distribution facts on wages over the life cycle in our NLSY data. In particular, we target the fact that for non-college males the mean wage rate grows by a factor of 2.44 between ages 17 to 40 and that for college individuals the average wage grows by a factor of 2.28 between ages 23 to 40. For each education group, the calibration also targets the age-profile of the variance of log-wages and of the ratio of the mean to median wages by minimizing a loss function.[12] For the non-college type we use wage data on individuals aged 17 to 40; while for college type we use wage data on individuals aged 23 to 40.

4.2 Calibration for Females

Preference for Children and Fertility Opportunities For each educational type, we select the preference parameter for the number of children γ_n to match the total fertility rate in the NLSY79 data. We assume that fertility opportunities are constant within four age groups but differ by number of children (0, 1, 2, and 3 or more).[13] We parameterize fertility opportunities with 7 parameters: 4 parameters describing fertility opportunities for the first child and 3 parameters scaling fertility opportunities by age conditional on having one, two, and three or more children. These parameters are chosen to match birth rates by age and the distribution of females at age 40 by number of children. The parameter values obtained in the calibration are reported in Table 3.

[11] Since the model period is 1 quarter, we choose values for $\sigma_z = 0.111/4$ and $\mu_z = -0.029/4$ in the model.

[12] Note that while Huggett et al. (2011) target facts on the earnings distributions, we target facts on the wage distribution. We target wages because labor hours are endogenous in our model.

[13] The four age groups are: 17-21, 22-26, 27-31, and 32-40 for the calibration of non-college women and 20-24, 25-29, 30-34, and 35-40 for the calibration of college women

Value of Staying at Home We assume that v_c is drawn from an exponential distribution with mean μ_{v_c}. For each educational type, the parameter μ_{v_c} is selected so that the model is consistent with the duration distribution of non-employment spells of mothers.

Labor Participation Cost We assume that females face a higher cost of full time work than males. In particular, the cost of participating full time by females is equal to the one of males but adjusted up by a factor which is greater than one and depends on the number of children (N) and the number of children less than age 6 N_6:

$$k_f(j, n_f, h, \kappa, N, N_6) = k_m(j, n_f, h, \kappa) \ [c_g + c_N N + c_{N6} I(N_6)],$$

where the parameter $c_g \geq 1$ is a gender factor increasing the cost of full-time work for all females, $c_N \geq 0$ gives the increase in the full-time participation cost per child faced by mothers, and $c_{N6} \geq 0$ gives the effect of children aged less than 6 years on full-time-participation cost of mothers, and $I(N_6)$ is an indicator which takes value 1 if $N_6 > 0$.

Summarizing, we need to calibrate the following parameters affecting female full-time participation cost: (c_g, c_N, c_{N6}). This is done using an indirect inference approach:

1. We run, for each education group, the following (Probit) regression in the NLSY data:

$$Pr(Y = 1/X) = \phi(X\beta), \tag{4}$$

   where $Pr(Y = 1/X)$ denotes the probability that employed females work part time), X denotes a vector of controls and ϕ the cumulative distribution function of a standard normal distribution. The vector of controls includes number of children, a dummy variable for the presence of a child less than age 6, and a full set of age dummies.

2. For a given guess on the parameters (c_g, c_N, c_{N6}), we simulate the model economy and run the (Probit) regression above in the model-simulated data.

3. We iterate on parameter values until the estimated marginal effects of children, children younger than age 6, and the predicted probabilities of part time employment (conditional on employment) are sufficiently close to the estimates obtained using NLSY79 data.

We emphasize that because of the interaction between fertility and labor market decisions, the calibration is a multidimensional procedure that involves iterating in all the female-specific parameters jointly (fertility opportunities, taste for children, and the parameters determining female participation costs).

4.3 Calibration Results

We now discuss how the model matches the calibration targets.

4.3.1 Results on Males

The model matches well the life-cycle path of male employment in the data for both education groups. To match the low employment rate early in the life cycle, the calibration requires that the cost of participation to be relatively large at young ages. This is because young individuals have strong incentives to work in order to accumulate human capital on the job (for instance, $k_{17} = 0.31$ and $k_{30} = 0.19$ for non-college and $k_{23} = 0.208$ and $k_{30} = 0.189$ for college). The model matches the calibration targets for the fraction of individuals in the NLSY data working part time in the non-college (about 10%) and college population (16%) by imposing that part time work is less costly than full time work ($c_m(n_f) = 1$ and $c_m(n_p)$ equals 0.59 for non-college and 0.55 for college males).

Individuals in the model economy may alternate periods of work with periods of no participation because participation costs are subject to random shocks. Naturally, the incidence and duration of non-employment spells depends on the stochastic process of the shocks, specifically on the persistence and variance of innovations of the assumed auto-regressive process. These parameters were chosen so that the model delivers a distribution of non-employment spells that is close to the one in the data, as documented on Table 5. Note that the model is consistent with the fact that for both education groups about half of the non-employment spells last less than two quarters and about 20% of these spells last two quarters. The model matches reasonable well the average labor market experience accumulated over the life cycle for both education groups (adding periods of employment during ages 17 to 40 for non-college and ages 20 to 40 for college individuals). By age 40, the model implies a stock of accumulated experience of 18.6 years for non-college and 17.8 years for college, while this statistic in the data takes values of 17.9 and 17.2 years for the two education groups considered. Moreover, for each education group, the distribution of years of experience across the population compares well with the data (see Table 4).

The model predicts wage growth over the life-cycle because human capital and time worked $(n - n_i)$ increase with age. Quantitatively, the predictions of the model align well with the data. Non-college individuals in the model see their wage increased by a factor of 2.4 between age 17 to 40, which matches the calibration target in the data exactly. The model also matches well the facts on wage growth for college individuals. It predicts that between ages 23 to 40 the average wage is multiplied by a factor of 2.27, which matches the calibration target of 2.28.

At a qualitative level, our theory features two mechanisms that generate an increase in earnings dispersion over the life cycle. First, the heterogeneity in learning abilities cause the slope of the wage profile to differ across individuals. Individuals with high learning ability choose to accumulate more human capital relative to low learning ability individuals. Second, human capital shocks are a source of increasing dispersion in wages as individuals age. Figure 5 compares the age profiles of the variance of log-wages and of the ratio of mean wage to the median wage (skewness of the distribution of wages) in the calibrated model economy with those in the NLSY data for the two educational groups. Overall, the theory matches pretty well the increase of these two statistics over the life cycle. As in Huggett et al. (2011), the calibrated model needs substantial heterogeneity in the initial human capital and learning ability in order to match these facts. Moreover, the calibration requires these two variables to be positively correlated in the population with a correlation coefficient of about 65%, which is close to the one found by Huggett et al. (2011).

Summing up, the calibrated model economy matches well the calibration targets for males. Moreover, despite the differences in model economies, the parameter values of the human capital technology in the calibrated model economy are consistent with the ones in Huggett et al. (2011) (Note that these authors did not model variation in labor supply decisions across individuals).

4.3.2 Results on Females

Our calibration strategy assumes that females are endowed with the same human capital technology as men: Both genders face an identical Ben-Porath technology with returns to scale of $\alpha = 0.70$ and the same (log-normal) distribution of learning abilities. In order to be consistent with the observed wage gap at labor market entry in the NLSY data (about 9% for non-college and 12% for college relative to the average wage of males), the mean of the initial distribution of human capital is assumed to differ across genders. The mean of the distribution of initial human capital of females is chosen to match the gender wage gap at labor market entry. The calibration implies that females enter the labor market with lower human capital than males.[14]

The model is calibrated to match fertility statistics and the impact of children on female labor supply. Table 6 shows that the model matches quite closely the average fertility rates in the data for both education groups (1.95 for non-college and 1.54 for college females), the distribution of birth rates by age, and the distribution of number of children across females at age 40. For non-college females, the model implies that the fraction of females at age 40 with no children is about 14% in the model (same figure in the data) and about 31% in the case of non-college females (slightly over 27% in the data). The mean utility value of spending time at home with children after giving birth (v_c) is calibrated so that the model is consistent with the duration distribution of non-employment spells of mothers. The calibrated model does a pretty good job in matching this distribution. Table 8 shows that roughly, both in the model and in the data, about 20% of non-employment spells last one quarter and about one half of them last more than a year.

The female-specific parameters affecting the cost of full-time work are calibrated using an indirect inference approach.[15] Table 7 presents the estimated marginal effects of children on the probability of working part time (conditional on employment) in the NLSY and model-simulated data. Marginal effects are computed for each female in the sample and averaged over all the population. We find that, both in the NLSY and model simulated data, the presence of children younger than age 6 has an important effect on the probability of working part time for both education groups. In the NLSY data, young children are associated with a rise in the the probability of working part time of 5 percentage points for non-college mothers and 7 percentage points for college mothers. The corresponding marginal effects in the NLSY

[14] The variance of initial human capital and the correlation between ability and initial human capital is kept constant across genders. The log of initial human capital is normally distributed. For non-college individuals, the calibration implies $\mu_{h0} = 2.22$ for males and $\mu_{h0} = 2.04$ for females. For the college educated, the calibration implies $\mu_{h0} = 4.32$ for males and $\mu_{h0} = 4.15$ for females.

[15] In the baseline model economy, children increase the cost of participating in the labor market for mothers through two parameters. Each child increases the participation cost in full time work by 0.051 for non-college and by 0.11 for college relative to the participation cost of a male (which is normalized to 1). In addition, having children less that 6 years increases the cost of full time work in 0.04 for non college and by 0.075 for college. There is also a gender factor that increases the participation costs of females relative to males, regardless of the number of children that females may have. This factor is 0.05 for non-college and .01 for college females.

data are 4 and 9 percentage points. Furthermore, we find that the number of children have an important impact in the incidence of part time employment both in the NLSY and model-simulated data. In the NLSY data, an increase in the number of children is associated with an increase in the probability of working part time of 5 percentage points among non-college women and 8 percentage points for the college educated females. In the model economy, these marginal effects are 7 percentage points for non-college and 4 percentage points for college mothers.

The table also reports the predicted probabilities of part time work for non-college and college females. These probabilities are 20% for non-college and 22% for college in the NLSY data and are closely matched by the model.

Overall, the model produces fertility histories of non-college and college women that align well with the NLSY data. The duration distribution of non-employment spells of mothers predicted by the theory is also consistent with the evidence. Both in the NLSY and model-simulated data, children are associated with large negative effects in the probability of employment of mothers and with a rise in the probability of working part time.

5 Quantitative Analysis.

In this section, we use our theory to measure human capital investment by females. We analyze the interactions between fertility, labor supply, and human capital investment decisions and we study how these interactions are shaped by the heterogeneity in learning abilities among females.

Interaction of fertility, labor supply, and human capital decisions Fertility decisions interact in non-trivial ways with human capital accumulation and labor supply decisions. Human capital investments and labor market decisions are jointly determined because human capital is accumulated on the job and because its return depends on future labor supply decisions. Fertility decisions are also jointly determined with the labor supply and investment decisions because children increase the cost of work and may lead to a reduction in expected future hours of work and, hence, in the returns to human capital accumulation. In a life cycle framework, the interdependence across decisions is particularly strong for young females for two reasons: First, fertility opportunities are more likely to arise for young women and they tend to decrease over the life cycle. Second, the returns to human capital accumulation tend to decrease monotonically with age. Hence, females make fertility choices during a period in the life cycle when the incentives to work and accumulate human capital are strong.

Figure 6 graphs the average life-cycle profile of human capital investments in the baseline economy by gender and education. The figure shows the annual mean hours devoted to human capital accumulation by individuals with positive hours of work during the year. Hours are normalized so that 0.40 represents the total working time of a year round full-time worker. Note that in the standard Ben-Porath model − with no endogenous labor supply decisions − investment time decreases monotonically over the life cycle. However, in our Ben-Porath model with endogenous labor supply decisions the investment profile on Figure 6 is hump shaped. Human capital investments increase with age for young individuals because hours of work increase during the first years of the life cycle.

The age-profile of human capital investments of females is below that of males for all ages. The profiles plotted on Figure 6 reveal that even at age 20 − when few females are mothers − there are sizable gender differences in human capital investments. Young females have weaker incentives to invest in human capital than males because their expected lifetime labor supply is lower that that of males. Gender differences in lifetime labor supply are more important among non-college than college individuals, which accounts for the higher gender differences in investments at age 20 among non-college than college people. The gender differences in human capital investments grow substantially as females aged and give birth to children, reaching a peak around age 24 for the non-college group, and age 28 for the college group. In understanding these investment patterns, it is important that college females exhibit lower fertility and become mothers at a later age than non-college women. After reaching its peak, gender differences in human capital investments decrease monotonically and are close to zero by age 50.

Learning ability and female decisions It is interesting that the interactions between fertility, labor market, and investment decisions vary substantially across females with different abilities. Females with high learning ability, everything else equal, face higher returns to human capital accumulation than the average ability-person in the population, making them more willing to work long hours in order to accumulate human capital and less likely to give birth and diminish their labor market attachment after becoming mothers. As a result, fertility decisions vary across non-college females of different learnings abilities in our baseline economy. While the mean number of children among age-40-women is 1.94, this statistic varies from 2.1 to 1.88 as ability increases. The median age at first birth increases by almost two years as ability increases from the lowest to the highest level. Intuitively, high ability women tend to delay the birth of the first child and to bear fewer children in order to minimize the impact of children on their lifetime labor supply and human capital accumulation.

The heterogeneous impact of children on labor supply across mothers with different learning abilities can be assessed by partitioning the population of non-college females in two learning ability groups of roughly equal size − a low and a high learning ability group. For each group, we then estimate the probability that employed females work part time conditional on the number of children, a dummy for the presence of children younger than age 6, and a full set of age dummies (as done in the calibration of the baseline economy). We find that the marginal effect of children in the probability of part time employment (conditional on employment) is much larger for non-college females in the low ability group: The presence of a child aged less than 6 years increases the probability of part time employment (conditional on employment) by 5 percentage points for the low ability group and by 2.7 percentage points for the high ability group. The effect of the number of children on part time work is also higher for the low ability group, by about 2 percentage points. We also estimate that the predicted probability of employment (whether part time of full time work) differs substantially across the two groups of non-college females, taking values of 65% and 74% for the low and high ability groups, respectively.[16]

The interaction between fertility, labor supply, and human capital accumulation is also important among college females. This is illustrated in a counterfactual experiment that

[16]This effect is assessed by running a Probit regression on the probability of employment.

simulates the behavior of college fenales assuming that they exhibit the distribution of learning abilities of non-college females. We find that the total fertility rate of college females increases from 1.54 to 2.12. The fact that college females on average display a higher learning ability than non-college females, diminishes their incentives to give birth to children. The distribution of learning abilities also generates important differences in fertility behavior across college females. When we partition college females in two groups − a low and a high ability groups − we find that the average fertility rate is 2.2 for the low ability group and 0.8 for the high ability group. The changes in fertility are mainly driven by the fraction of females with no children, which is much larger for the high ability than the low ability group (58% versus 5.4%). The impact of children on their mother's labor supply is also quite heterogeneous across college females. Using a Probit analysis − similar to the one done for non-college females − we find that the marginal effect of children on the probability of part time employment is much larger for females in the low ability group: The presence of a child younger than age 6 increases the probability of part time work (conditional on employment) by 13 percentage points and 3.6 percentage points for college females in the low and high ability groups. The marginal effect of the total number of children is also higher (by about 8 percentage points) for the low ability group. Furthermore, the predicted probability of employment (whether part time or full time) is 68% and 90% for the low and high ability groups, respectively.

Female wage growth and the gender wage gap Having shown that the theory implies important gender differences in human capital investments we now ask: Can the theory quantitatively account for the substantial gender differences in the life-cycle wage growth documented in the NLSY data? The answer to this question is yes. In fact, for non-college individuals we find that the wages of females grow over the life cycle slightly less in our model than in the data. While between age 17 to age 40 the wages of non-college females grow by a factor of 1.95 in the data, they grow by a factor of 1.84 in the model. Thus, the model can account for all the differences in gender wage growth among the non-college population. For college individuals, wages of females between age 23 to age 40 grow by a factor of 1.77 in the data and by a factor of 1.98 in the model. Thus, the theory over predicts the wage growth of college females by about 20 percentage points. The gender differences in wage growth lead to an increase in the gender wage gap over the life-cycle. In the model, the rise in the gender wage gap for non-college individuals between ages 17 to 40 is equal to 22 percentage points (19 percentage points in the NLSY data). For college individuals, the wage gap between ages 23 to 40 rises in the model by 12.5 percentage points relative to the 19.5 percentage points in the NLSY data, so that the model accounts for about two thirds of the increase in the wage gap among college individuals in the NLSY data.

Learning ability and the gender wage gap The relationship between the life-cycle increase in the gender wage gap and learning ability has an inverted U-shape. Focusing on non-college individuals and partitioning them in three learning-ability groups, the increase in the gender gap is 10 percentage points for the lowest-ability group, 29 for the middle-ability group, and 12 percent for the highest-ability group.[17] The intuition for this result is as follows.

[17]In the baseline economy there are 10 ability groups ordered from lowest to highest. We group them into three categories: the lowest includes levels 1-3, the middle includes the levels 4-6 and the rest is included in

Females invest less in human capital than males as they expect to work fewer hours. If the gender differences in hours of work were exogenously fixed across different ability groups, we should expect the growth in the gender wag gap over the life cycle to increase with the ability of individuals. However, hours of work are endogenous and vary across ability groups in a non-random fashion. Because individuals with high learning ability face a higher return to human capital investments, the endogeneity of labor supply and fertility decisions implies that females of high ability will make decisions to minimize the impact of children on their labor market attachment. As a result, relative to the average female, females of high ability tend to give birth to fewer children, delay the timing of birth, and they are less likely to interrupt their careers or to work part time after giving birth. Hence, the gender differences in labor supply and investment behavior decrease with the learning ability. This mechanism accounts for why rise of the gender wage gap over the life cycle decreases with learning ability among individuals at the top of the ability distribution.

5.1 Testing predictions of the theory

It is interesting to evaluate the predictions of the theory for the wage growth for two groups that partition the female population: females with no children by age 40 (females with no kids ever) versus females that are mothers by age 40. In the NLSY data wages of non-college women with no kids ever grow between ages 17 to 40 by 115%, while for females with children they grow by 81%. In the model data, the corresponding statistics are 115% and 78%. By age 40, the wage ratio between these two groups of females is 1.20 in the NLSY data and 1.18 in the model-simulated data. Thus, the predictions of the model match remarkably well the corresponding statistics in the data. The model is less successful in matching the data for college women. While both in the NLSY and in the model economy college women with no children ever exhibit higher wage growth relative to mothers, the model overestimates the wage growth of non-mothers between ages 23 to 40 by a large margin: It predicts a wage growth of 200% while in the data this statistic is 87%. In the model economy, college females with no kids ever are self-selected from the highest ability groups. Our results indicate that in the baseline economy non-mothers are too strongly positively selected from the distribution of learning ability. To match the data, it seems that the model needs to allow for some mechanism that makes women with high ability more willing to give birth to children, such as (unobserved) heterogeneity in preference for children across college women or perhaps modeling marriage. Such extensions of the model are likely to predict a higher gender wage gap for college female, as high ability female will be less insulated from the impact of children on their labor supply. These extensions of our present work are left for the future.

The theory predicts that females of high learning ability are likely to bear fewer children, to be older at the birth of their first child, work more, and accumulate more human capital than the average female in the population. While the learning ability is essentially an unobserved variable, there is a prediction of the theory that we can test on the NLSY data. The theory predicts that wage growth across females should be positively correlated with the age at which they become mothers. We test this prediction in two ways.

Test 1. For each education group (college and non-college), we group women in the NLSY

the highest category.

data by the age when they give birth to their first child. Next, we compute the average annual wage growth over the life cycle (up to age 40) for each woman in the NLSY data. We then compute the correlation between the wage growth up to age 40 and the age of mothers at first birth. We find that these two variables are positively correlated, with a correlation coefficient of 0.80 for non-college and 0.48 for college women. When this procedure is repeated in the model simulated data we find correlation coefficients of 0.85 and 0.71 for non-college and college women.

Test 2. One may suspect that the positive correlation between wage growth and the age of mothers at first birth is just reflecting the fact that women who become mothers at a later age have invested more in human capital than the average female in the population of mothers. While this is consistent with the theory, a stronger test of the theory arises by focusing on how wage growth of females before they become mothers correlates with the age of mothers at first birth. The idea is that if learning ability is important for fertility and human capital accumulation decisions, then we should expect that the (annual) average wage growth of mothers − prior to giving birth to their first child − to rise with the age at which women become mothers. If this is true in the NLSY data, it will support the idea that women who give birth to their first child at a later age are of a relatively high learning ability, as predicted by the theory.

We group women by the age that they give birth to their first child. Next, for each mother in the NLSY data, we compute the average annual wage growth over the life cycle up to one year before becoming mothers for the first time. Unlike Test 1, by focusing on annual wage growth to the previous year of becoming mothers, we ensure that wage growth differences across women are not driven by the effect of children (or pregnancy) on the labor supply of mothers. In this way, we focus on wage growth differences that are caused by learning ability differences, either because learning ability directly affects the return to human capital investments or because it causes higher human capital investments. We then compute the correlation between the annual wage growth before motherhood and the age of mothers at first birth. We find that these two variables are positively correlated in the NLSY data for both education groups, with a correlation coefficient of 0.45 for non-college and 0.74 for college women. When this procedure is repeated in the model simulated data we find correlation coefficients of 0.56 and 0.70 for non-college and college females, respectively.

5.2 Race and the Gender Wage Gap

While in the U.S. black women tend to have more children than white women, the gender wage gap is lower among blacks than among non-blacks. At first glance, this observation seems inconsistent with the predictions of our theory. Nonetheless, we now show that the theory is qualitatively consistent with data on gender differences in wage growth across races. We use NLSY data (with the oversample of blacks) to document some facts on gender differences in labor supply and wages among black individuals. Due to small sample sizes, the analysis is restricted to individuals with non-college education. The main findings are:

- FACT 1: Black non-college women tend to have more children and to give birth at younger ages than the average non-college woman. The total fertility rate of non-college black women is 2.28 while it is 1.95 for non-college women (including all races). The timing of births also differs across black and the average non-college woman. About 30% of births occur before age 20 for black non-college women while such percentage is 18% for all non-college women.

- FACT 2: The labor supply of black non-college women is lower than the labor supply of the average non-college women. The accumulated experience at age 40 (in hours) is 13 years for black non-college women while it is 14.5 years for the average non-college woman.

- FACT 3: The gender wage gap at age 40 is lower among non-college black than among the average non-college population. While at age 17 the gender wage gap is small and does not vary across races, the gender wage gap at age 40 is 15 percentage points among black non-college while it is 23 percentage points among all non-college individuals.

The first two facts point that black women tend to have more children (at young ages) and to work less than the average non-college women, which is consistent with the view that children negatively affect the labor supply of females. Hence, our theory implies that black females should face lower incentives to accumulate human capital than the average non-college female in the U.S. economy. It is thus surprising that the gender differences in wage growth in the U.S. are smaller for blacks than for non-blacks individuals (Fact 3). We now document two more facts that help reconcile the predictions of the theory with the U.S. data.

- FACT 4: Gender differences in labor supply are lower for non-college blacks than for all non-college individuals. The ratio of experience (measured by adding up lifetime hours of work) at age 40 of men relative to women is 1.32 for black non-college individuals and 1.45 for all non-college individuals.

- FACT 5: Life-cycle wage growth is lower for black non-college women than for the average non-college women. Between age 17 to age 40 wages grow by a factor of 1.77 for black non-college women and by a factor of 1.95 for all non-college women.

Fact 5 shows that black non-college women face lower wage growth than the average non-college woman. Despite the low wage growth of black non-college women, by age 40 the gender wage gap among black non-college individuals is smaller than that of the overall non-college population (Fact 3). The low gender wage gap for blacks is explained by the fact that black males work very little and accumulate little human capital relative to other males in the U.S. economy (Fact 4). Thus, the low gender wage gap among black non-college individuals does not contradict our view that children have a negative impact on female wage growth. In fact, consistently with our theory, the data reveals that black women work less (Fact 2) and accumulate less human capital (Fact 5) than the average non-college woman in the economy. Our theory points that black females face low returns to human capital accumulation because they expect to have more children and, hence, to work less than other non-college females in the economy.

6 Conclusions

The Ben-Porath (1967) model is extended to measure how much of the gender wage gap over the life cycle is due to the fact that working hours are lower for females than for men. The theoretical framework incorporates labor supply and fertility decisions into an otherwise standard Ben-Porath model. It is assumed that there are no gender differences in the human capital technology or in the distribution of learning abilities but that the bearing and presence of children increase the cost of full time work of females. The calibration uses an indirect inference approach to ensure that the estimated impact of children on the labor supply of mothers in the model economy is consistent with the one estimated in the US data. The quantitative theory is used to measure human capital investments by females over the life cycle. We find that the theory accounts for all of the increase in the gender wage gap over the life cycle in the NLSY79 data for non-college females and for about two thirds of the increase in the gender wage gap of college females. We find that the learning ability matters importantly for the interaction between fertility, labor market, and investment decisions. Females with high learning ability face higher returns to human capital accumulation than the average ability-person in the population, making them more willing to work long hours in order to accumulate human capital and less likely to give birth. The impact of children on mother's labor supply is also quite heterogeneous across females of different learning abilities, with females of high learning ability being less likely to diminish their labor market attachment after becoming mothers relative to the mean female in the population. In future work, it would be important to investigate how differences in occupational choices matter for gender differences in hours of work and human capital accumulation. It will also be interesting to use an extended version of our framework to analyze how various factors affecting female labor supply over time impact on the gender wage gap. To deepen our understanding of the family and welfare, the model could be enhanced to incorporate a non-linear utility function on consumption together with savings and marriage decisions. These interesting but non-trivial extensions are left for future research.

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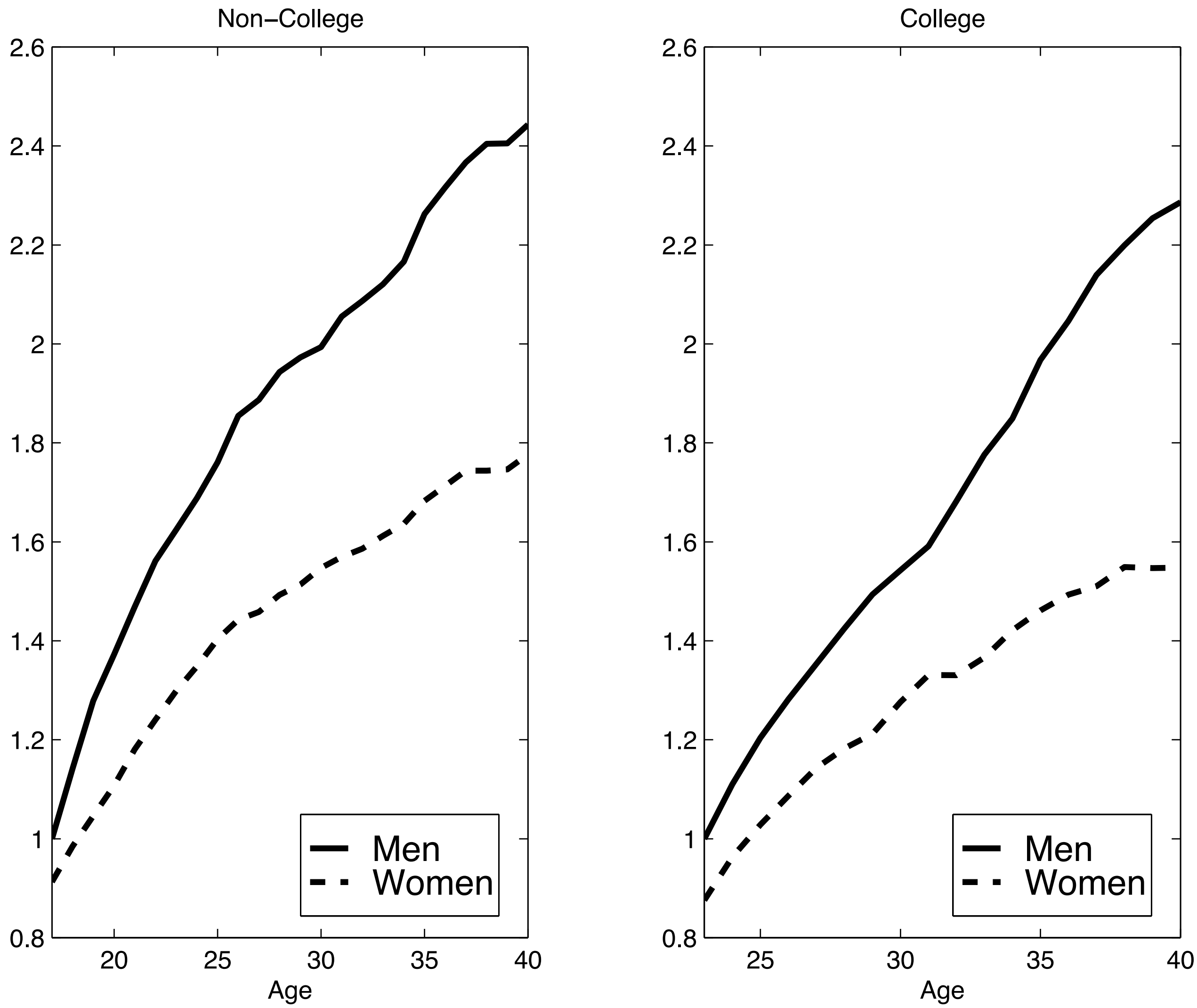
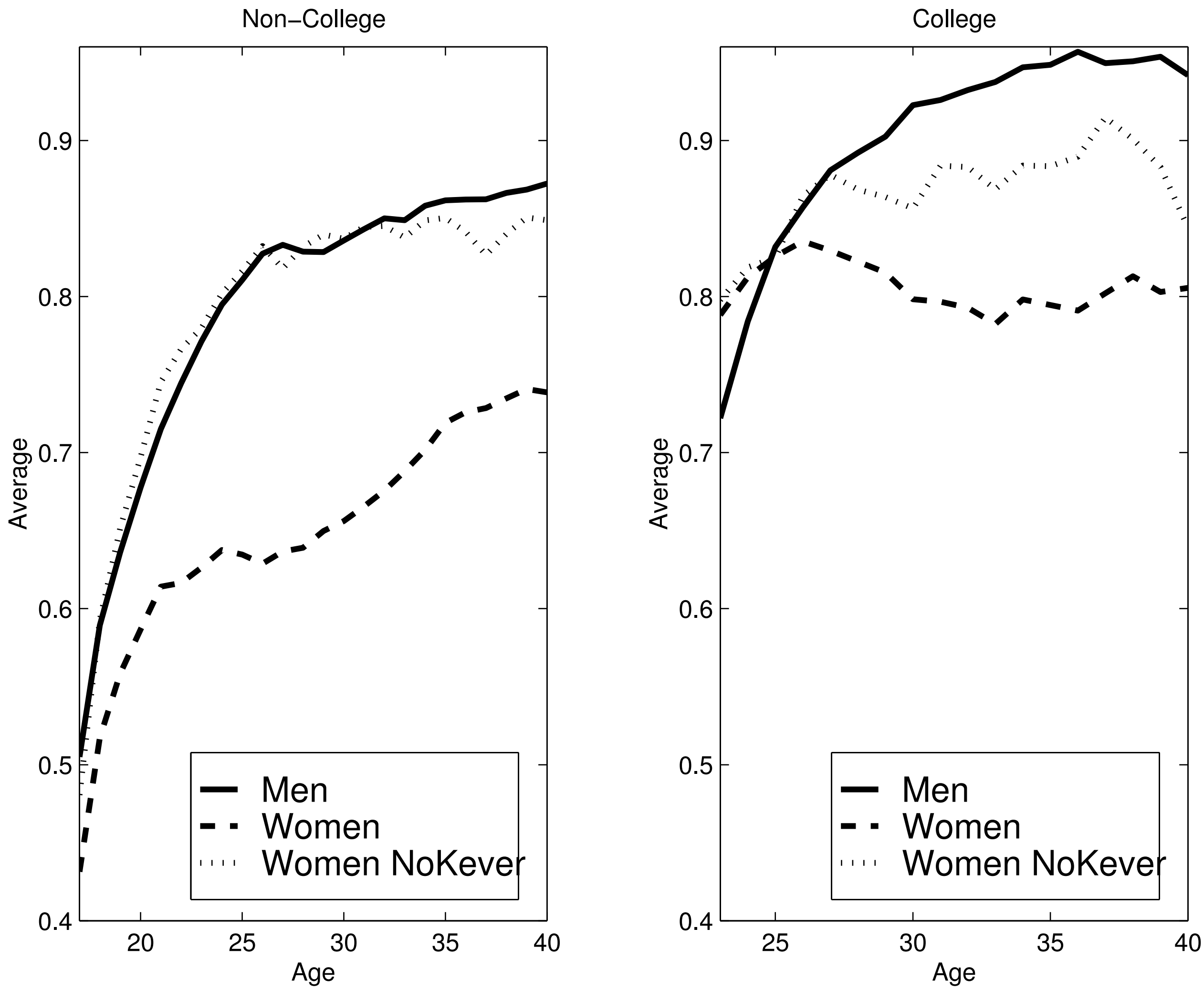
Figure 1: Average Hourly Wage by Age



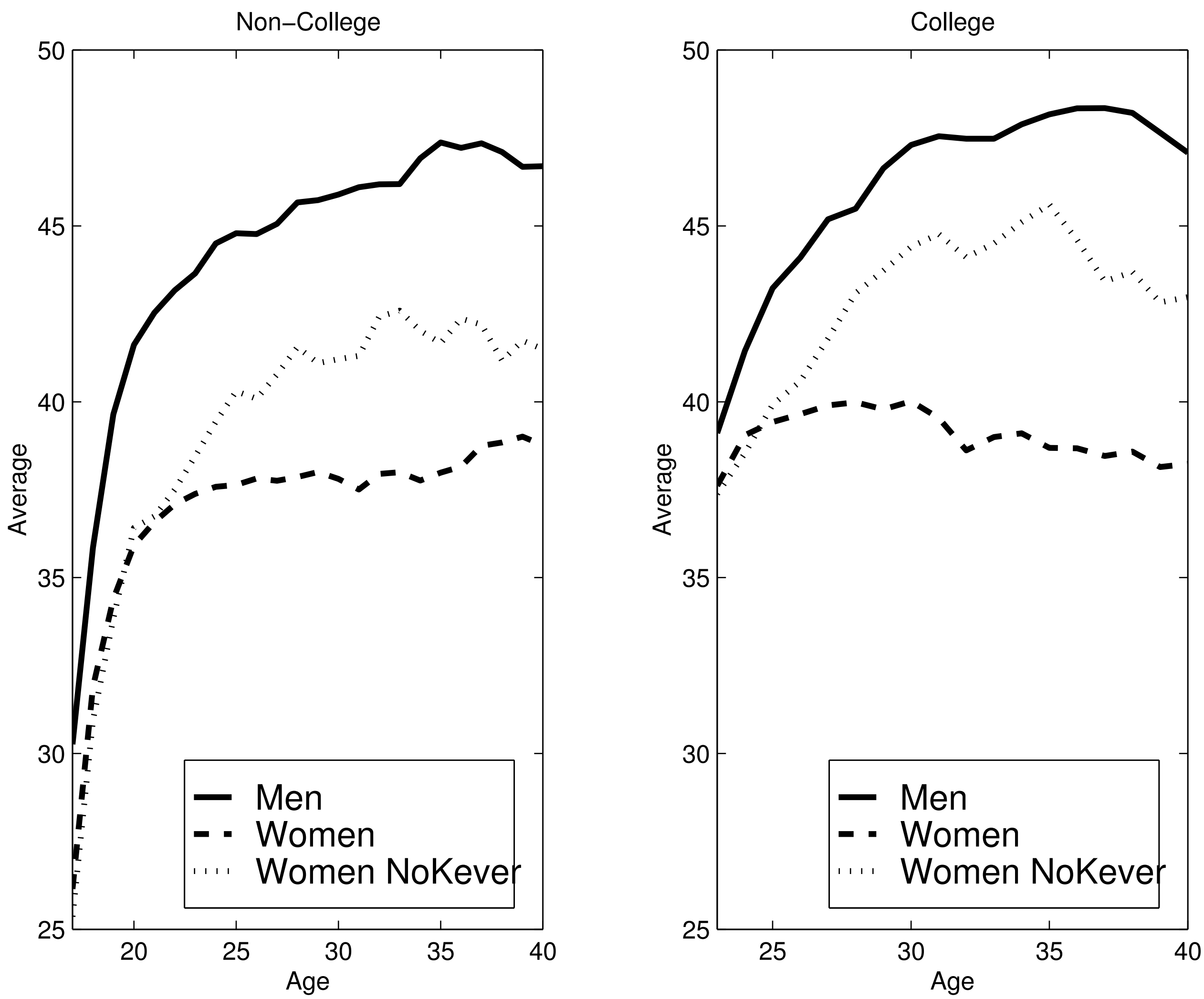
Relative to the average wage of men at initial age.

Figure 2: Employment to Population Ratio



Women NoKever refers to women with no children (until the last observation in our sample, when women are between 36 to 43 years of age).

Figure 3: Hours Per-worker (per-week)



Women NoKever refers to women with no children (until the last observation in our sample, when women are between 36 to 43 years of age).

Figure 4: Employment rate around birth

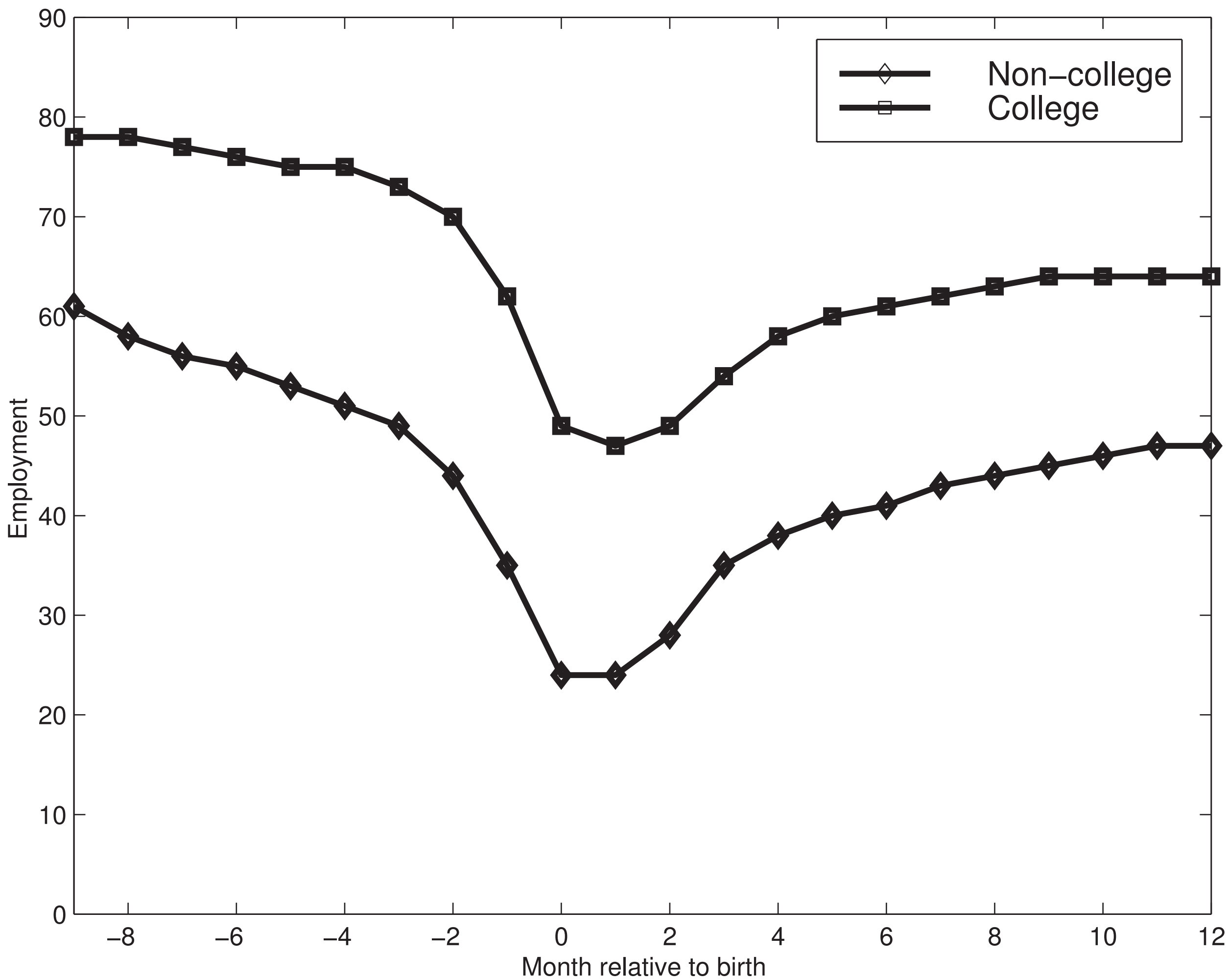


Figure 5: Wage Statistics -Males

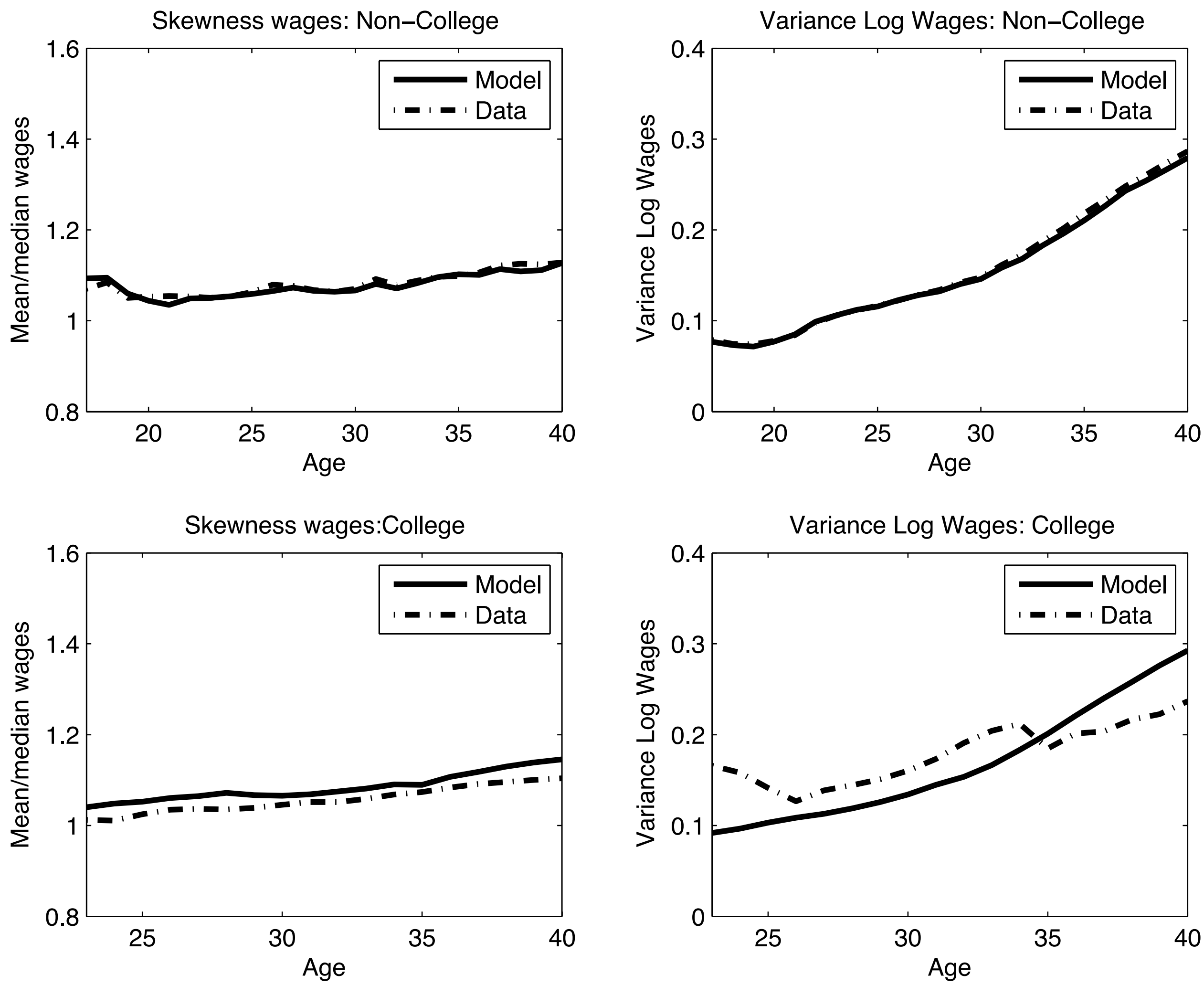


Figure 6: Investment

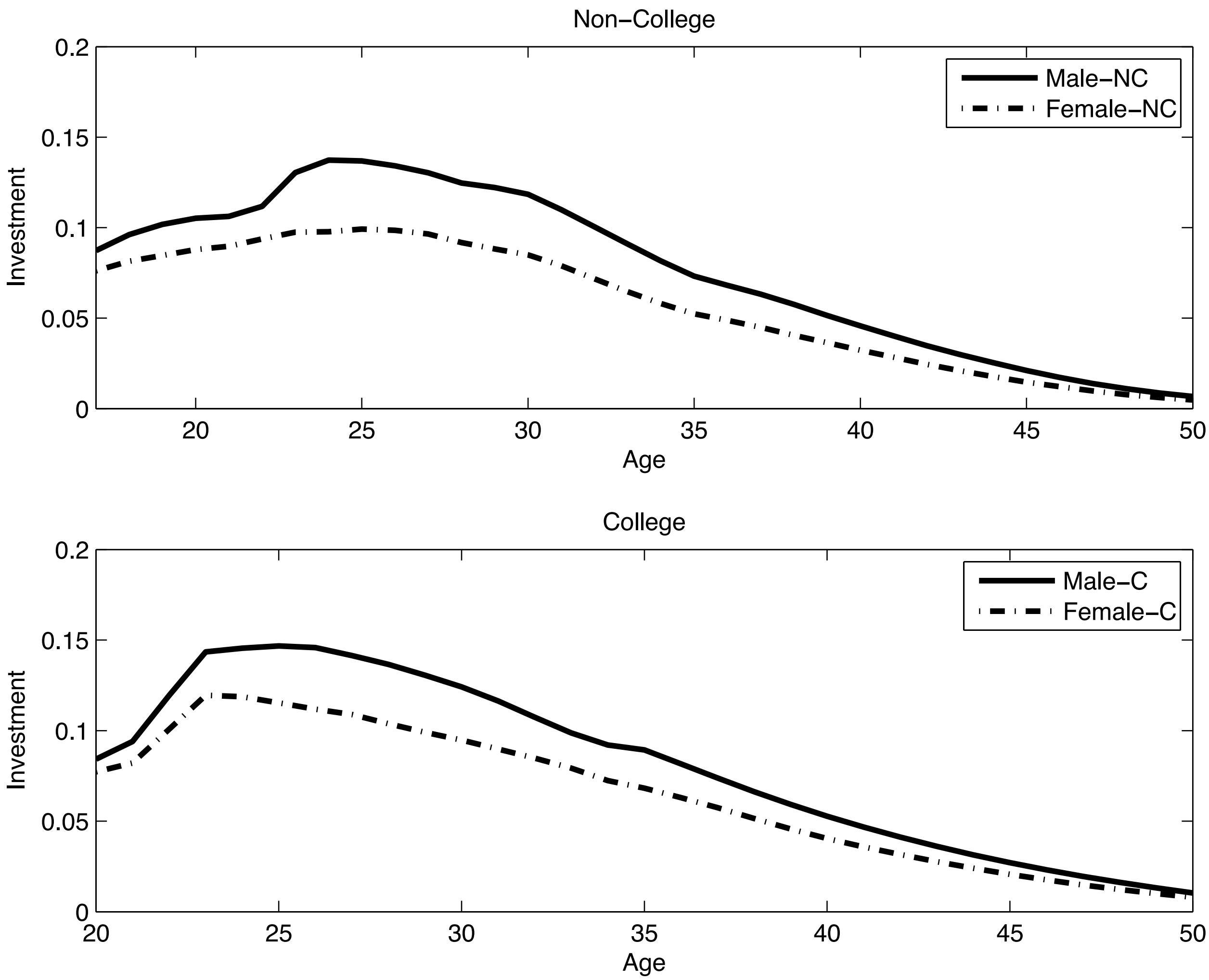


Table 1: Duration of Non-Employment Spells

	Non-College				College			
	Men	Women	Women		Men	Women	Women	
			No birth	birth			No birth	birth
Average (weeks)	45.6	73.8	50.4	113.4	41.6	60	38	102
Distribution (%):								
1 quarter (7-19)	46	37	42	19	49	52	57	30
2 quarters (20-32)	20	16	18	10	18	12	13	11
3 quarters (33-45)	11	10	11	9	11	9	10	9
4 quarters (46-58)	6	7	7	8	7	5	6	5
More than a year (>58)	17	30	22	54	15	22	14	45

Table 2: Accumulated Experience at Age 40 (years)

	Non-College		College	
	Weeks	Hours†	Weeks	Hours†
Men (M)	18.7	21.0	19.3	20.9
Women (W)	15.3	14.4	17.6	16.4
Ratio M/W	1.22	1.45	1.10	1.27
Women:				
No Children	16.6	16.7	18.5	18.6
Children	14.8	13.7	17.3	15.7

†Refers to equivalent years corresponding to 52 weeks and 40 hours of work per week.

Table 3: Parameter Values

Non-College				College			
Parameter	Value	Parameter	Value	Parameter	Value	Parameter	Value
k_{17}	0.31	σ_z	0.0277	k_{20}	0.326	σ_z	0.0277
k_{20}	0.31	μ_z	-0.0072	k_{21}	0.322	μ_z	-0.0072
k_{25}	0.25	α	0.7	k_{23}	0.208	α	0.7
k_{30}	0.19	$\theta^{17-21}(0)$	0.0269	k_{25}	0.196	$\theta^{20-24}(0)$	0.0123
k_{40}	0.19	$\theta^{22-26}(0)$	0.0265	k_{30}	0.189	$\theta^{25-29}(0)$	0.0378
k_{50}	0.19	$\theta^{27-31}(0)$	0.0265	k_{40}	0.191	$\theta^{30-34}(0)$	0.06216
k_{55}	0.19	$\theta^{32-40}(0)$	0.0090	k_{50}	0.191	$\theta^{35-40}(0)$	0.03182
k_{60}	0.25	$\theta^j(1)$	$\theta^j(0) * 1.44$	k_{60}	0.20	$\theta^j(1)$	$\theta^j(0) * 14.8$
k_{65}	0.28	$\theta^j(2)$	$\theta^j(0) * 0.76$	k_{65}	0.2	$\theta^j(2)$	$\theta^j(0) * 0.27$
$c_m(n_p)$	0.59	c_g	1.05	$c_m(n_p)$	0.5513	c_g	1.01
c_N	0.051	c_{N6}	0.04	c_N	0.11	c_{N6}	0.075
ρ	0.52	$\theta^j(3+)$	$\theta^j(0) * 0.76$	ρ	0.5	$\theta^j(3+)$	$\theta^j(0) * 0.48$
σ_v	0.3	μ_{v_c}	0.065	σ_v	0.3	μ_{v_c}	0.065
$\sigma_{h_{17}}$	0.277	γ_n	1.2	$\sigma_{h_{20}}$	0.36	γ_n	1.7
$\mu_{h_{17}}$	2.22 (2.044)	χ	0.5	$\mu_{h_{20}}$	4.32 (4.15)	χ	0.5
σ_{ab}	0.212	$corre_{ab,h_0}$	0.644	σ_{ab}	0.256	$corre_{ab,h_0}$	0.644
μ_{ab}	-1.74			μ_{ab}	-1.27		

Table 4: Distribution of Accumulated Experience - Males

	Non-College*		College**	
	Data	Model	Data	Model
Average (years)	17.9	16.9	17.2	17.16
Distribution (%):				
<17 years	29.6	23	31.6	33
$[17, 19)$ years	18	31	41.1	38
$[19, 23)$ years	51.4	45	27.3†	29†

*Between ages 17 and 40. **Between ages 20 and 40. †Between 19 and 21 years of experience.

Table 5: Duration Distribution of Non-employment Spells- Males (%)

	Non-College		College	
	Data	Model	Data	Model
1 quarter	46	46.5	49	49.1
2 quarters	20	22.6	18	21.7
3 quarters	11	12.3	11	11.6
4 quarters	6	6.8	7	6.5
More than a year	17	11.7	15	10.9

Table 6: Fertility Rate, Birth Rates by Age, and Distribution of Females at Age 40 by Number of Children

	Non-College		College	
	Data	Model	Data	Model
Average Fertility	1.95	1.94	1.54	1.54
Birth Rates: (%)				
17-19	17.5	17.5	2.1	
20-24	32.5	29.8	11.0	14.5
25-29	28.4	27.2	31.7	36.1
30-34	15.1	15.6	37.3	35.3
35-40	6.5	9.9	17.9	14.1
Female Distribution by Number of Children: (%)				
0	14.0	14.8	27.3	31
1	18.6	18.5	14.4	12.2
2	35.2	35.6	37.7	36
3	20.5	19.9	13.8	12.5
≥4	11.2	11.2	6.8	8.3

Table 7: Probit Regression: Part-time work

	Non-College		College	
Variable	Data	Model	Data	Model
Children	0.054	0.07	0.08	0.04
Children less than 6	0.051	0.04	0.072	0.09
Predicted P	0.20	0.20	0.22	0.20

All coefficients are significant at any significance level.

Table 8: Duration Distribution of Non-employment Spells of Mothers (%)

	Non-College†		College*	
	Data	Model	Data	Model
1 quarter	19	22	28	20
2 quarters	10	12	10	13
3 quarters	9	9	9	11
4 quarters	7	7	6	9
More than a year	55	50	47	47

†Between ages 17 and 40. *Between ages 20 and 40.