# A Quantitative Theory of the Gender Gap in Wages[†]

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Abstract

Using panel data from the National Longitudinal Survey of Youth (NLSY), we document that gender differences in wages almost double during the first 20 years of labor market experience and that there are substantial gender differences in employment and hours of work during the life cycle. A large portion of gender differences in labor market attachment can be traced to the impact of children on the labor supply of women. We develop a quantitative life-cycle model of fertility, labor supply, and human capital accumulation decisions. We use this model to assess the role of fertility on gender differences in labor supply and wages over the life cycle. In our model, fertility lowers the lifetime intensity of market activity, reducing the incentives for human capital accumulation and wage growth over the life cycle of females relative to males. We calibrate the model to panel data of men and to fertility and child related labor market histories of women. We find that fertility accounts for most of the gender differences in labor supply and wages during the life cycle documented in the NLSY data.

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# 1 Introduction

A striking but well known feature of the U.S. labor market is that the average hourly wage of women is much lower than that of men. Less known is the fact that the gender gap in wages grows over the life cycle. These gender differences in wages over the life cycle are accompanied by substantial gender differences in labor supply, mostly due to the impact of children on the labor supply of women.

The goal of this paper is to build a quantitative theory of fertility, labor supply, and human capital accumulation decisions in order to understand the wage and labor supply of women over the life-cycle and why they differ from those of men. We develop a decision-theoretic framework in which individuals decide how much effort to exert in accumulating human capital on the job and whether to work or to stay at home. Females make fertility decisions which negatively affect their labor supply. While it is clear that any theory of gender differences needs to introduce some differences between male and females, there are many ways one could introduce gender differences. Our approach is to assume that the bearing and presence of children involves a forced reduction in hours of work that falls on females rather than on males. We then use our theory to assess the role of children in understanding gender differences in labor supply and wages over the life cycle.

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) stress the importance of modeling human capital and labor supply decisions jointly in a life-cycle framework. Two crucial insights from these seminal papers are that the incentives to accumulate human capital vary along the life cycle and that these incentives 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 Polachek (1974). These authors provide evidence that married women tend to interrupt their labor market attachment with periods of non-participation and, using a regression framework, they find that expected career interruptions do have an impact on the human capital investments of young women. While intuitively appealing, the insights of Mincer and Polachek have not been formally modeled in a decision-theoretic framework. In fact, Killingsworth and Heckman (1986) in their survey on female labor supply, refer to the work of Mincer and Polachek as the "informal theory". One way of viewing our contribution is to provide an explicit model of the "informal theory" and to evaluate its quantitative importance for understanding the wages and the labor supply of women over the life cycle.

We use panel data – the 1979 cohort of the National Longitudinal Survey of Youth (NLSY79) – to document observations characterizing the labor market behavior of a recent cohort of young men and women. Our starting point is that there are substantial gender differences in labor supply and that these differences are closely related to the impact of children on the labor supply of women. We document that the average number of hours of work per person is about 40% larger for men than for women between the ages of 20 and 40. By age 40, this difference in hours of work translates into a stock of accumulated experience that is about 50% larger for men than for women.[1] We also find that the primary factor

[1]We emphasize that gender differences in cumulative hours of work are much larger than the ones obtained

in understanding gender differences in labor supply is given by children. In particular, once we condition by the number of children, marriage is not crucial for understanding the low working hours of women. Human capital theory implies that gender differences in hours of work should translate into different incentives for human capital accumulation across genders. The data lends supports to the importance of human capital accumulation as a determinant of wages since there is substantial wage growth during the first 20 years of labor market experience − wages of men more than double between age 20 and age 40. Moreover, our data suggest that differential human capital accumulation can be a source of gender differences in wages since the life cycle wage growth of women is lower than that of men. We document that the gender gap in wages almost doubles from age 20 to age 40 − from about 18 percentage points at age 20 to 32 percentage points at age 40. This increase in the gender gap in wages over the life cycle occurs despite substantial convergence in average wages between men and women during the period (see Blau and Khan, 2000).

We emphasize the importance of modeling human capital accumulation in a life cycle framework (with a realistic life span). This approach allows us to better compare the statistics of our model with the data, which is of first-order importance in quantitative theory. Moreover, theory suggests that the incentives to accumulate human capital are driven by the life-cycle profile of working hours, not just by the average amount of hours worked. In particular, to the extent that young females may not know the exact path of future labor supply, investment in human capital depends on expected lifetime labor supply. The un-

by focusing on years of employment, which is the measure of experience typically used in empirical studies. Moreover, we find large gender differences in hours of work, even among full-time workers. This illustrates an advantage of the NLSY, relative to other data sources such as CPS or PSID, in providing week-by-week data on hours of work.

certainty associated with future fertility implies gender differences in labor supply, human capital accumulation, and wages over the life cycle even among males and females with similar (ex-post) age-profiles of employment. The question that we answer in this paper is how much.

We calibrate the model to panel data of men and to fertility and child-related labor market histories of women. Our quantitative theory is successful in matching our calibration targets. In particular, our theory matches the age-profile of employment and the age-profile of hours of work for men. We use panel data of men, regarding wages and labor supply, to calibrate the human capital technology. We assume that there are no gender differences in the human capital technology and we use our quantitative theory to measure human capital accumulation by females over the life cycle. Regarding females, our model replicates the birth rates by age and the impact of children on career interruptions and labor supply. We find that fertility generates gender differences in employment and hours that lead to differential returns to experience across genders and a wage gap that increases with age. Our theory implies that the gender wage gap grows 21 percentage points between ages 20 and 40, a figure that is actually larger than the one in the data (in Section 5 we discuss what may explain this result). We find that (at least) 40% of the increase in the gender gap in wages between ages 20 and 40 is due to the impact of children on the labor supply of females and that our theory implies a gap in wages between mothers and non-mothers that is consistent with the data. Children have a large negative effect on wages of females because they reduce the labor supply at a stage of the life cycle when the returns to human capital accumulation on the job are high.

Our theory emphasizes the importance of future labor supply as opposed to actual experience for human capital accumulation. Our findings are consistent with the vast empirical literature that finds a substantial gender residual in wage regressions that measure human capital investments by past experience. To illustrate this point, in one experiment we simulate males and females in our model that are identical in terms of initial human capital and lifetime employment. Our simulated males and females only differ in lifetime labor supply because females work 10% less hours than males and because females expect to have children −with the associated negative impact on labor supply− even though ex-post no female is ever given an opportunity to have children. As a result, we simulate females that are identical to males at age 20 and have identical age-profile of employment over the life cycle. Since females in this experiment work more than 35 hours a week, we follow the empirical literature in counting them as full-time employed. We find that the gender wage ratio in this experiment is exactly 1 at age 20 and despite no differences in lifetime full-time employment, at age 40, females earn on average a wage that is 9 percentage points lower than the average wage of males. Using this simulated data, a standard wage regression of log wages on experience (measured as full-time employment) and a sex dummy as explanatory variables, would attribute a negative wage effect to being a female worker and a lower return to (measured) experience by females relative to males. This experiment shows that even females that are highly attached to the labor market face weaker incentives to invest in human capital than males that can generate sizeable gender wage gaps. We conclude that, in the context of our framework, standard statistical decomposition analysis of the gender gap in wages produces misleading results.

There is a recent literature using quantitative theory to explain the decrease in the gender gap in wages during the last 25 years in the U.S. labor market (see Olivetti, 2001 and Jones, Manuelli, and McGrattan, 2003). While our theory can be used to analyze recent time trends, our focus in this paper is on the level of the gender gap in wages for a recent cohort of young men and women and the impact of children in gender differences in labor supply and wages. Bowlus (1997) estimates a search model in order to assess the role of gender differences in expected labor market turnover for understanding the gender wage gap, an exercise that is similar in spirit to ours. A distinguishing feature of our approach, relative to previous papers in the literature, is that we use a life-cycle model with a realistic lifespan. As a result, we can use detail panel data to parameterize the human capital technology. Huggett, Ventura, and Yaron (2004) is the paper closest to ours in terms of methodology since they also use panel data to restrict the human capital technology in a life-cycle model. Our paper differs from theirs in that we focus on gender differences in wages. Moreover, in our theory actual labor market experience is not a sufficient statistic for human capital growth since, due to unobserved effort, returns to experience are endogenous. Imai and Keane (2004) estimate a dynamic life-cycle model of human capital accumulation but their interest is in estimating the inter-temporal elasticity of substitution of labor supply rather than the gender differences in wages. Attanasio, Low, and Sánchez-Marcos (2004) and Greenwood, Seshardi, and Yorukoglu (2005) focus on understanding time trends in female labor supply. Da Rocha and Fuster (2004) use quantitative theory to investigate recent cross-country observations on fertility and female labor market participation rates.[2]

[2]More generally, our paper follows a recent tradition in quantitative theory on the economics of the family

Our paper also relates to the literature on wage differences between mothers and non-mothers (see for instance Anderson, Binder, and Krause, 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, Fuster, and Restuccia (2001, 2002) argue that these features can account for only about 10 to 20% of the family gap in wages. Differently than the large wage losses associated 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 where 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 section 5, 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

initiated by Aiyagari, Greenwood, and Guner (2000) and Regalia and Ríos-Rull (1998).

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 2000, people in our sample are between 36 to 43 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.

**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. Figure 1 documents the increase in the average wage over the life cycle for both men and women. Whereas the average wage of men increases by a factor of 2.1 over the span of 20 years (from age 20 to age 40), the average wage of women increases by a factor of 1.7: The difference in wage growth is in average a one percentage point per year during this time span. The implication of this differential wage growth over the life cycle is that the gender wage ratio decreases from 0.82 at age 20 to 0.68 at age 40. In other words, the gender gap in wages increases by 14 percentage points over the early part of the life cycle. (See Figure 2.)[3] Notice also that there is a substantial gender gap in wages near the entry to the labor market, a gender gap in wages of about 18 percentage points. The evidence of wage growth over the life cycle points to the importance of investment in human capital: In average men more than double their wage in 20 years. This is relevant for understanding the gender gap in wages (and its growth over the life cycle) because the returns to human capital investment depend on the dedication of time to the labor market 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. Therefore, in order to understand the gender gap in wages, it is essential to document the gender differences in labor supply between men and women and their origins.

**Employment and Hours** Men work in average 40% more hours than women (37.6 vs. 26.7 hours per person per week, see Table 1). 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).[4]

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[3]The increase of the gender gap in wages over the life cycle is even larger for highly educated people in narrowly defined occupations. For instance, Wood, Corcoran, and Courant (1993) document wage differences between male and female graduates of the University of Michigan Law School. While the gender differences in earnings in the first year after graduation are almost negligible, the average hourly wage ratio between these men and women is 0.67 after 15 years of graduation. Moreover, O'Neill (2003) documents that men and women in the NLSY79 data are roughly similar in standard measures of education and qualification test scores.

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

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

Table 1: Average Hours and Employment

| | Men | Women | |
|---|---|---|---|
| | | All | No Child† |
| Hours per person (week) | 37.6 | 26.7 | 33.9 |
| Hours per worker (week) | 45.9 | 38.7 | 41.3 |
| Employment to population ratio | 0.82 | 0.69 | 0.82 |

People 20 to 43 years of age. †No Child refers to women with no children (until the last observation in our sample, when women are between 36 to 43 years of age).

Figures 3 and 4 document the life-cycle path of average hours per-worker and the employment to population ratio for men and women. 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 5 percentage points higher for men than for women at age 20, by age 40 this difference is 12 percentage points. There is also a substantial gap in hours of work among people working: At age 20, employed men spend 6 hours more working per week than women. At age 40 the difference in hours of work is 8 hours per week.

An alternative way of characterizing differences in hours and employment between men and women is by looking at the overall distribution of hours of work. Table 2 documents the distribution of hours of work for men and women: Employment and jobs associated with more than 40 hours of work per week are more prevalent among men than among women.

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

Table 2: Distribution of Hours (%)

| | Men | Women | |
|---|---|---|---|
| Hours per week: | | All | No Child† |
| Zero | 17.6 | 30.6 | 17.8 |
| 1-39 | 10.0 | 23.3 | 21.1 |
| 40 | 33.5 | 29.4 | 35.2 |
| >40 | 39.0 | 16.7 | 25.9 |

People 20 to 43 years of age. †No Child refers to women with no children (until the last observation in our sample, when women are between 36 to 43 years of age).

**Characteristics of Non-Employment Spells** Employment is more prevalent among men than women over the life cycle, but both men and women face spells of non-employment and therefore it is of interest to characterize the gender differences in the spells of non-employment. Even though the average number of non-employment spells and its distribution are similar between men and women, the duration of non-employment spells differs across genders: A non-employment spell lasts in average 41 weeks for men and 65 weeks for women − on average non-employment spells last six months longer for women than for men.[5] Compared to men, non-employment spells of women are more concentrated among spells of long duration: 27% of the non-employment spells of women last more than a year. (See Table 3.)

**The Accumulation of Experience** Women are characterized by lower employment, fewer hours of work, and longer duration of non-employment spells than men. These gen-

[5]The NLSY79 data follows a cohort of young people, therefore, average duration and number of spells are not comparable to averages of other samples that include older workers. We restrict our sample to include histories of people that at the start of any spell is 20 years of age or older and we abstract from spells of short duration (6 weeks or less).

Table 3: Duration of Non-Employment Spells

| | Men | Women | Women No childbirth | Women Childbirth† |
|---|---|---|---|---|
| Average (weeks) | 41 | 65 | 44 | 104 |
| Distribution (%): | | | | |
| 1 quarter (7-19) | 48 | 41 | 46 | 23 |
| 2 quarters (20-32) | 18 | 15 | 17 | 10 |
| 3 quarters (33-45) | 12 | 10 | 11 | 9 |
| 4 quarters (46-58) | 6 | 7 | 7 | 7 |
| More than a year (>58) | 16 | 27 | 19 | 51 |

Excludes non-employment 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.

der differences in labor supply imply that on average, women accumulate less experience in the labor market than men. Table 4 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.[6] Table 4 indicates that by age 40, men have accumulated 24% more weeks of experience than women, and 48% more hours of work than women. These differences in experience are substantial: Women would require a much higher return to experience in order to exert the same effort in accumulating human capital than men. Moreover, the differences in experience reported in Table 4 are substantial even if compared with commonly used measures of experience such as potential experience (age-years of schooling-6) or actual experience (accumulated years of employment).

[6]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 4 assume these cases as zero hours, but alternative assumptions yield similar results.

Table 4: Accumulated Experience at Age 40 (years)

| | Weeks | Hours† |
|---|---|---|
| Men (M) | 18.6 | 20.9 |
| Women (W) | 15.0 | 14.1 |
| Ratio M/W | 1.24 | 1.48 |
| Women: | | |
| No Children | 17.8 | 18.3 |
| Children | 14.4 | 13.3 |

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

**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 that never had children.[7] 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 3. The pattern of average hours per worker is also similar between men and women with no children except for a constant gap (roughly 6 hours per worker per week or about 10% of the hours per worker of males). This pattern of hours of work for women with no children is reported in Figure 4. Comparing the distribution of hours of work between men and women without children reveals the same pattern reported in Figures 3 and 4 for men and women over the life cycle: Employment is as prevalent for women without children as for men, but women with no children tend to work less hours per week than men.

[7]For the last observation of every woman in our sample – when they are between 36 to 43 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).

Children have lasting effects on employment and hours of women. Table 5 decomposes hours per person, hours per worker, and the employment to population ratio for men and for women differing by the number of children and by the age of their children. Differences in employment to population ratios across women are striking: While women with no children under 18 years of age have an average employment to population ratio similar to the average of males (81.2% vs. 82.6%), women with one child under 18 years of age or more have employment to population ratios below 65%. The employment ratio of women with young children (less than a year old) is less than 50%. As documented earlier, men work 40% more hours than women. Part of the difference in average hours comes from the effect of children on labor supply of women: Average hours worked per person for women decline with the number of children, specially for women with children less than 6 years of age and average hours is specially low for women with young children (less than a year old). In average, children reduce hours per worker of women in about 4% per child. Labor hours differ substantially by the age of the child, although differences in hours per worker are not as marked as employment for women with young children compared with men. In particular, 70% of the difference in hours per person between men and women with young children is accounted for by the difference in the employment to population ratio while the remaining 30% is accounted for by the difference in hours per worker.

Children have an important impact in the duration of non-employment spells of women (see Table 3). We divide all non-employment spells of women between spells that involve the birth of a child at the time or during the job separation (we call these spells "Childbirth") and spells that do not involve the birth of a child ("No Childbirth"). An important fraction of

Table 5: Average Hours and Employment

| | Hours/Person | Hours/Worker | Employment Ratio |
|---|---|---|---|
| Men | 37.6 | 45.6 | 82.6 |
| Women | 26.7 | 38.5 | 69.5 |
| Women by Number of Children under 6: | | | |
| 0 | 31.1 | 39.6 | 78.3 |
| 1 | 21.7 | 36.3 | 59.5 |
| 2 | 16.0 | 34.3 | 46.4 |
| 3 or more | 11.3 | 34.1 | 32.8 |
| Women by Age of Youngest Child: | | | |
| Less than 3 months | 11.6 | 35.3 | 32.8 |
| 3 to 6 months | 15.2 | 34.6 | 43.8 |
| 6 to 9 months | 16.4 | 34.6 | 47.6 |
| 9 to 12 months | 17.0 | 34.6 | 48.9 |
| 1 to 5 years | 20.4 | 35.8 | 56.7 |
| 5 to 6 years | 24.5 | 37.4 | 65.5 |

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 (44 weeks). The main difference in the duration of non-employment spells between men and women is in the spells of women that involve the birth of a child (104 weeks vs. 41 weeks for men).[8] These gender differences in the duration of non-employment spells translate into differences in accumulated experience (see Table 4). Men and women with no children accumulate about the same amount of experience, however, women with children accumulate much less experience than men, 24% in weeks and 48% in hours.

[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). For employed mothers around the birth of a child, 57% remain employed, 21% return to work within a quarter, 12% return to work after a year, and 3% never return to work.

**Marriage or Children?** While many authors have emphasized the importance of marriage for understanding female labor supply, our reading of the data is that the primary factor affecting labor hours of women is children. The evidence already discussed in Table 5 points to the importance of the number and age of children for labor supply of women. To assess the relative importance of children and marriage in understanding gender differences in labor supply, we report in Table 6 the accumulated weekly hours of experience by gender, marital history, and children for people of age 35 or 36. The table shows that when we focus on women without children, the difference in accumulated years of experience between men and women is not affected by whether women have ever been married or not. Children do have an important impact on labor supply of women: While childless women accumulate about 10% less hours of experience than men (regardless of marital status), women who had a child before age 36 accumulate about 30% less hours of experience than men. When we consider women with children, marriage is associated with higher (not lower) labor supply relative to men. In our sample, never married women with children have the lowest accumulated experience relative to men. Mincer and Polachek (1974) report similar observations for an older cohort of men and women in the U.S.: The average number of years of non-participation since school is 10.4 and 3.3 for white married women with and without children, respectively.

Table 6: Accumulated Experience − Marriage vs. Children

| | Hours | |
|---|---|---|
| | Years | Ratio |
| Men | 16.3 | 1.00 |
| Women "No Children": | | |
| -Ever married | 14.5 | 0.89 |
| -Never married | 14.4 | 0.88 |
| Women "Had Children": | | |
| -Ever married | 11.0 | 0.68 |
| -Never married | 8.8 | 0.54 |

People 35 or 36 years of age. Experience is weekly hours of work converted into years by dividing for 52 weeks and 40 hors per week. "No children" refers to women that at the specified age has not had a child and "Never married" refers to women who at the specified age has never been married.

# 3 Economic Environment

We consider a life-cycle economy populated by male and female workers. In each period people decide whether to work or stay at home and, if they work, they choose an amount of effort in accumulating human capital. Females also make fertility decisions. To keep our analysis simple, we abstract from marriage, inter-temporal consumption smoothing, and general equilibrium interactions. Below we present the key ingredients of our framework.

**Life-Cycle** People enter the labor market at age 20 and may decide to work up to age 65. We emphasize that modeling a finite lifetime allow us to capture the life-cycle aspect of fertility and human capital accumulation decisions. Our model generates life-cycle observations for employment and wages that can be compared with data.

**Labor Decision** We model the labor participation decision by assuming that people draw a stochastic value of staying at home, which could be correlated over time and vary with age and, in the case of females, with the number of children. People decide whether to work a fixed amount of hours (that depends on the age, gender, and number of children of that person) or not to work. In making the employment decision, people face the following trade-off: If they work, they earn labor earnings, which enter linearly in their utility function but they do not enjoy the entire utility of staying at home. The trade-off also has a dynamic component since we assume that human capital is accumulated while working.

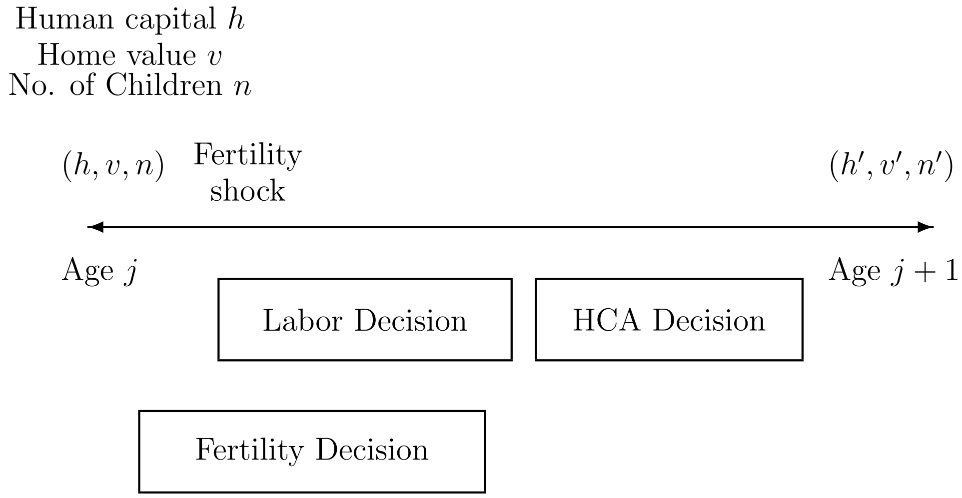
**Human Capital Accumulation Decision** We model human capital accumulation while working. We assume that workers who exert effort $e$ increase their human capital by a proportion $\triangle$ with probability $e$. The utility cost of effort is given by $c(j, h)\log(1 - e)$, where $c(j, h)$ is a function of the age and human capital of the person. Roughly speaking, the parameter values describing the utility cost of effort $c(j, h)$ are selected to match age and experience profile of wages for people at different points of the wage distribution. Studies in the psychology literature point that the ability to learn decreases with age, suggesting that the cost of accumulating human capital increases with age.[9] We also allow for the possibility that spending time at home is more valuable for high human capital people. Finally, we assume that the wage rate is proportional to human capital.

**Fertility Decision** We assume that females derive utility from children and from spending time with them at home. Therefore, children can have a negative impact on the employment

[9] See for instance Avolio and Waldman (1994) and Skirbekk (2003).

decision of females. In addition, we assume that children reduce the hours of work of females by an exogenous amount per child. 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.

**Timing of Decisions** Below, we draw a time line representing the timing of decisions within a period in our model. People start an age-$j$ period with a state given by the value of staying at home $v$ and an amount of human capital $h$. In addition, females start the period with a given number of children $n$ and a fertility shock. In a first stage, females who have a fertility opportunity decide whether to give birth or not. Males and females without fertility opportunities do not take any decisions in this stage. In a second stage, people decide whether to work a fixed amount of hours (that depends on the age, gender, and number of children of the person) or not to work. In a third stage, working individuals decide how much effort to exert in accumulating human capital. People who do not work during the current period enjoy the value of staying at home. At the end of the period, individuals make a new draw for the value of staying at home (which is assumed to be correlated over time).




We formalize the decision problem of a female using the language of dynamic programming. The decision problem of a male is similar but without the fertility stage. An age-$j$ female starts the period with a state given by human capital $h$, number of children $n$, and home value $v$. She then faces a fertility opportunity with probability $\theta^j(n)$. Her value function, prior to the realization of the fertility opportunity, is represented by $B^j(h, n, v)$ and satisfies,

$$B^j(h, n, v) = \theta^j(n) \max \left\{ V^j(h, n+1, v), V^j(h, n, v) \right\} + (1 - \theta^j(n)) V^j(h, n, v),$$

where the max operator represents the fertility decision and $V^j$ denotes the value function of a female after the fertility stage. The labor market decision is represented as follows:

$$V^j(h, n, v) = \max \left\{ W^j(h, n, v), H^j(h, n, v) \right\},$$

where $W$ denotes the value of working and $H$ the value of staying at home. $W^j$ is given by,

$$W^j(h, n, v) = hl(j, n) + (1 - l(j, n)) u(h, v) + \gamma_n \log(1 + n)$$

$$+\max_{e\in[0,1]}\left\{c(j,h)\log(1-e)+e\hat{V}^i(h(1+\triangle),n,v)+(1-e)\hat{V}^i(h,n,v)\right\},$$

where $l(j,n)$ denotes the fraction of hours worked by a female of age $j$ and $n$ children, $hl(j,n)$ represents labor earnings, $u(h,v)$ is the value of staying at home which is allowed to depend on human capital and the value of staying at home $v$, and $\gamma_n$ is a parameter determining taste for children for females. If the worker exerts effort $e$, at a utility cost of $c(j,h)\log(1-e)$, the worker increases human capital to $h(1+\triangle)$ with probability $e$. The function $\hat{V}^j$ is the expected discounted value of a female prior to the realization of the value of staying at home next period. This value evolves over time according to a transition function $Q_j$ (which depends on the age of the worker),

$$\hat{V}^j(h',n,v)=\beta\int_{v'}B^{j+1}(h',n,v')Q_j(dv',v).$$

The value of not working $H$ is given by,

$$H^j(h,n,v)=u(h,v)+\gamma_n\log(1+n)+\beta\int_{v'}B^{j+1}(h,n,v')Q_j(dv',v).$$

People who do not work enjoy the entire value of staying at home $u(h,v)$. We assume that human capital does not depreciate when not working.

# 4 Calibration

Our calibration strategy is as follows. We calibrate the model 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, and the growth in wages over the life cycle. We emphasize that heterogeneity and life-cycle profiles in wages are important for parameter values related to human capital accumulation. For females, we only calibrate to targets that relate to the number of children and to the employment and hours histories of women after childbirth. 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.

## 4.1 Calibration of Males

Some parameters are selected without solving the model. We set the model period to be a quarter and $\beta = 0.99$. Hours per worker for males, $l(j)$, 20 to 40 years of age are obtained from NLSY79 and for men 41 to 64 years of age, hours are obtained from CPS data. 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. We present a summary of parameters and targets in Table 7.

**Value of Staying at Home** We assume that the value of staying at home for a worker with human capital $h$ and home shock $v$ is given by $u(h,v) = hv$. We assume that $v = v_j v_s$, where $v_j$ represents a deterministic life-cycle value of staying at home and $v_s$ denotes a stochastic shock to the value of staying at home. The life-cycle term $v_j$ is used to generate a plausible age profile of employment. We search for 9 values of $v_j$ in order to match the employment rate of men at 9 selected ages (the values of $v_j$ for other ages are linearly interpolated). The stochastic component $v_s$ is used to generate flows in and out of employment. We assume that $v_s$ follows a first order autoregressive process: $v_{s'} = \rho v_s + \varepsilon_v$, where $\varepsilon_v \sim N(0, \sigma_v^2)$. The parameters $(\rho, \sigma_v)$ 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 that individuals enter the labor market at age 20 and that they make a draw of their initial human capital from a log-normal distribution. The mean of log human capital is normalized to 2 (the lowest log human capital is normalized to 0) and the standard deviation, $\sigma_{h_{20}}$, is chosen so that the coefficient of variation of wages for male workers at age 20 matches the 0.36 value in the NLSY79 data. For computational tractability we approximate the continuous log-normal distribution with a discrete distribution over 200 grid points. We assume that the disutility of effort varies with age and human capital according to the function $c(j,h) = \alpha(j)h^{\gamma_h}$ where $\alpha(j) = \alpha_1 + j^{\alpha_2}$ and $\gamma_h > 0$. The technology for accumulating human capital is then described by the growth rate $\triangle$, $\gamma_h$, and the parameters $(\alpha_1, \alpha_2)$. These parameters are selected in order to obtain age profile of wages for two groups of workers in the data. In particular, we focus on the average wage for people in the bottom and top 50% of the distribution of wages at each age.

Table 7: Calibration for Males

| Parameter | Target |
|---|---|
| $v_j$ | Employment by age |
| $\rho$ | Duration of non-employment spells |
| $\sigma_{\epsilon_s}$ | Average experience at age 40 |
| $\sigma_{h_{20}}$ | C.V. wage at age 20 |
| $(\alpha_1, \alpha_2, \Delta, \gamma_h)$ | Wage-age profiles for high and low wage people |

**Summarizing** We divide the set of calibrated parameters in two groups. The first group consists of those parameters that can be selected without solving the model. They include the time-discount rate and the profile of working hours by age. The second group consists of 16 parameters whose calibration requires solving the model. They are given by 9 parameters describing deterministic home values by age ($v_j$), 2 parameters describing the stochastic home values ($\rho, \sigma_\epsilon$), 4 parameters describing human capital accumulation ($\triangle, \alpha_1, \alpha_2, \gamma_h$), and one parameter for the initial distribution of human capital $\sigma_{h_{20}}$. We proceed by minimizing a loss function that adds the square deviations between the values of the statistics in the model and the values of the target statistics in the data. A summary of the parameter values obtained is shown in Table 9.

## 4.2 Calibration for Females

**Preference for Children and Fertility Opportunities** We select the preference parameter for the number of children $\gamma_n$ to match the total fertility rate in the NLSY79 data.

We assume that fertility opportunities are constant within the age groups 20-24, 25-29, 30-34, and 35-40 but differ by number of children (0, 1, 2, and 3 or more). 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. A summary of the parameters and the targets in the data is reported in Table 8 and a summary of the parameter values in the calibration is shown in Table 9.

**Value of Staying at Home** In order to model the impact of children on female employment and career interruptions, we assume that females derive utility from spending time at home with children. The value of staying at home for females is given by $v = v_j(v_s + v_c)$. The term $v_j$ represents a life-cycle (deterministic) value and $v_s$ is a stochastic value of staying at home as described in the calibration for males. The term $v_c$ is a stochastic value of spending time at home with children. We assume that females can enjoy $v_c$ when giving birth or during a child-related spell of non-employment. In other words, working females that have not given birth in the current period cannot quit their jobs to enjoy $v_c$. For computational simplicity, we assume that $v_c$ is drawn from an exponential distribution with mean $\mu_{v_c}$. The parameter $\mu_{v_c}$ is selected to match the employment ratio of women by the age of the youngest child.

**Hours of Work and Human Capital** We assume that the age profile of working hours for females is the same as the one for males but for the fact that females work in average

10% less hours than males (at every age) and that in average each child reduces the hours of work by 4% until age 40. These assumptions are motivated by our observations from the NLSY79 data discussed in Section 2. We assume that females face the same technology for accumulating human capital as males. We assume, however, that the distribution of human capital of females at age 20 is shifted to the left by an exogenous amount relative to the distribution of males. This assumption is motivated by the fact that in the NLSY79 data, the wages of women of age 20 are in average 18% lower than those of men of age 20. Since we do not model human capital decisions prior to age 20, our theory is not built to account for this initial gender difference in wages. We conjecture that part of this initial gap in wages is due to the same forces that we emphasize in our theory: Women expect to have children in the future and, thus, to work less hours than males. As a result, females invest less in market human capital not only after age 20, as emphasized in our theory, but also prior to age 20.

Table 8: Calibration for Females

| Parameter | Target |
|---|---|
| $\theta^j(n)$ | Distribution of number of children |
| $\gamma_n$ | Total fertility rate |
| $\mu_{v_c}$ | Employment of mothers by age of youngest child |

**Summarizing** We select the values of 9 parameters: 7 parameters describing fertility opportunities $\theta^j(n)$ at selected age groups and by number of children, the preference parameter for children $\gamma_n$, and the parameter describing the distribution for the value of staying at home with children $\mu_{v_c}$. As discussed for the case of the calibration of males, we proceed by minimizing a loss function constructed by adding the squared deviations between the statistics in the model with the corresponding target statistics in the data.

Table 9: Parameter Values

| Parameter | Value | Parameter | Value |
|---|---|---|---|
| $v_{20}$ | 2.40 | $\triangle$ | 3% |
| $v_{25}$ | 0.41 | $\alpha_1$ | 0.35 |
| $v_{30}$ | 0.36 | $\alpha_2$ | 0.35 |
| $v_{40}$ | 0.24 | $\theta^{20-24}(0)$ | 0.0231 |
| $v_{45}$ | 0.23 | $\theta^{25-29}(0)$ | 0.0236 |
| $v_{50}$ | 0.30 | $\theta^{30-34}(0)$ | 0.0189 |
| $v_{55}$ | 0.37 | $\theta^{35-40}(0)$ | 0.0113 |
| $v_{60}$ | 0.50 | $\theta^{j}(1)$ | $\theta^{j}(0) * 2.30$ |
| $v_{65}$ | 1.00 | $\theta^{j}(2)$ | $\theta^{j}(0) * 0.85$ |
| $\rho$ | 0.76 | $\theta^{j}(3+)$ | $\theta^{j}(0) * 0.60$ |
| $\sigma_{\epsilon}$ | 0.79 | $\mu_{v_c}$ | 3.2 |
| $\sigma_{h_{20}}$ | 0.33 | $\gamma_n$ | 1.0 |
| $\gamma_h$ | 0.78 | | |

## 4.3 Calibration Results

In what follows we describe the results of the model regarding the calibration targets discussed in the previous two subsections. Figure 5 reports the employment ratio by age for the model and the data. The model matches well the life-cycle path for male employment in the data. Together with the exogenous hours per worker, the life-cycle employment generates a stock of accumulated experience that compares well with the data. At age 40, the model implies 16.4 years of accumulated experience while the same statistic in the data is 16.8 years. This average experience is generated from a reasonable distribution of years of experience in the model relative to the data (see Table 10).

Figures 6 and 7 document the age and experience profile of wages for the model and

Table 10: Distribution of Accumulated Experience between age 20 and 40 - Males

| | Data | Model |
|---|---|---|
| Average (years) | 16.8 | 16.4 |
| Distribution (%): | | |
| $< 15$ years | 18 | 14 |
| $[15, 17)$ years | 17 | 31 |
| $[17, 19)$ years | 33 | 39 |
| $[19, 21)$ years | 32 | 15 |

the data for the average of people in the bottom 50% and in the top 50% of the age and experience distribution of wages. The model captures well the heterogeneity and the life-cycle pattern in average wage profiles for these two distinct groups of people. Moreover, the model also captures well the heterogeneity in wage growth by age at different points of the wage distribution for males (see Figure 8). Another target in our calibration procedure is the duration distribution of non-employment spells for men. Table 11 reports the duration distribution of these spells in the model and in the data.

Table 11: Duration Distribution of Non-employment Spells (%)

| | Males | |
|---|---|---|
| Duration (weeks): | Data | Model |
| 1 quarter (7-19) | 48 | 46 |
| 2 quarters (20-32) | 18 | 20 |
| 3 quarters (33-45) | 12 | 12 |
| 4 quarters (46-58) | 6 | 7 |
| More than a year ($> 58$) | 16 | 15 |

Regarding the statistics of our calibration targets for women with children, Table 12 reports the total fertility rate, birth rates by age, and the distribution of number of children for females at age 40. The average fertility rate is 1.84 children per female in the model and 1.81 in the data. The model also matches the birth rates by age and the distribution of women at age 40 by number of children: About 20% of females do not have children, 50% have one or two children, and 30% have 3 or more children.

Table 12: Fertility Rate, Birth Rates by Age, and Distribution of Females at Age 40 by Number of Children

| | Data | Model |
|---|---|---|
| Average Fertility | 1.81 | 1.84 |
| Birth Rates: (%) | | |
| 20-24 | 0.33 | 0.30 |
| 25-29 | 0.34 | 0.32 |
| 30-34 | 0.23 | 0.23 |
| 35-40 | 0.10 | 0.15 |
| Female Distribution by Number of Children: (%) | | |
| 0 | 19.0 | 20.0 |
| 1 | 17.3 | 13.5 |
| 2 | 35.8 | 36.7 |
| 3 | 18.2 | 22.2 |
| ≥4 | 9.7 | 7.6 |

Table 13 reports the employment to population ratio of females by age of the youngest child in the model compared with the data. The model matches well the pattern of low employment for females with young children.

Table 13: Employment Ratio of Mothers by Age of Youngest Child

| | Data | Model |
|---|---|---|
| Age of Child: | | |
| 1 quarter | 32.8 | 33.5 |
| 2 quarter | 43.8 | 44.4 |
| 3 quarter | 47.6 | 50.2 |
| 4 quarter | 48.9 | 54.2 |
| $[1, 5)$ years | 56.7 | 70.2 |
| $[5, 6)$ years | 65.5 | 82.3 |

Table 14 documents the duration distribution of child related non-employment spells in the model and in the data. The model implies slightly longer duration spells than in the data.

Table 14: Duration Distribution of Non-employment Spells of Mothers (%)

| Duration (weeks): | Data | Model |
|---|---|---|
| 1 quarter (7-19) | 20 | 18 |
| 2 quarters (20-32) | 10 | 10 |
| 3 quarters (33-45) | 9 | 8 |
| 4 quarters (46-58) | 7 | 6 |
| More than a year (> 58) | 54 | 58 |

# 5 Quantitative Analysis

In this section, we use our theory to measure human capital investment by females. Although we assume that females face the same human capital technology as males, there are three channels leading to gender differences in the returns to human capital investment. First, females expect to give birth to children which, in turn, negatively affects females' expected employment and working hours (young working mothers – 40 years old or less – work 4% less hours per child). Second, females work 10% less hours than males when employed (exogenous hour gap), regardless of whether they have children or not, as motivated by our discussion of the data in Section 2. Third, females at age 20 enter the labor market with a human capital that is 16% lower than the one of males (the gender gap in initial human capital is calibrated so that the model reproduces a gender gap in wages at age 20 of 18%, as documented in the NLSY79 data). As a result, our theory implies gender differences in human capital investments. The important question is whether our theory quantitatively accounts for the substantial gender differences in life-cycle wage growth documented in the NLSY data. Below, we argue that the answer to this question is yes.

**Female Labor Supply** As discussed in the calibration section, the model is calibrated to panel data of men and only to data of women that relates directly to the number of children and to the impact of children on women's employment and hours of work after childbirth. We emphasize that our calibration does not target the gender differences in labor supply. Table 15 reports the employment ratio of females for different ages in the model and in the data. Since the model implies higher female employment than in the data (specially among women older than 30 years), our findings suggest that there may be other factors, different from children, leading to the low employment rate of women relative to men (such as, household specialization). In addition, the model implies a slightly shorter duration of the non-employment spells of females relative to the data (see Table 16). Overall, the model generates large gender differences in labor supply, albeit smaller than in the data. In effect, by age 40, the gender difference in total hours of work in our model is about 31%, while this statistic is 48% in the data.

Table 15: Employment Ratio by Age - Females

| Age | Data | Model |
|---|---|---|
| 20 | 0.59 | 0.62 |
| 25 | 0.68 | 0.68 |
| 30 | 0.69 | 0.78 |
| 40 | 0.77 | 0.87 |

Table 16: Duration Distribution of Non-employment Spells† (%)

| | Females | |
|---|---|---|
| Duration (weeks): | Data | Model |
| 1 quarter (7-19) | 38 | 42 |
| 2 quarters (20-32) | 17 | 19 |
| 3 quarters (33-45) | 12 | 11 |
| 4 quarters (46-58) | 7 | 7 |
| More than a year (> 58) | 26 | 20 |

†Between ages 20 and 40.

Table 17: Average Accumulated Experience between ages 20 and 40 (in years)

| | Hours | |
|---|---|---|
| | Data | Model |
| Males | 19.2 | 19.0 |
| Females | 13.0 | 14.7 |
| Males/Females | 1.48 | 1.31 |

**Wages of Females in the Life Cycle** Our model of human capital investments can account for the low life-cycle wage growth of females relative to males. In fact, if anything, we find that the wages of females grow with age slightly less in our model than in the data. While in the data the wages of females grow between ages 20 to 40 by a factor of 1.75, in the model they grow by a factor of 1.65. Our theory also has implications for the cross-sectional distribution of wages along the life-cycle. We find that our model does a good job in accounting for the slow wage growth for female workers at the bottom 75% of the wage distribution (see Figure 9). The main disparity between the model and the data is that the model implies much slower wage growth for female workers at the top 10% of the wage distribution relative to the data. In Table 18, we show that the life cycle wage growth for the bottom 50% of the wage distribution is given by a factor of 1.40 in the data and by a factor of 1.36 in the model. Regarding the top 50% of the wage distribution, the life cycle wage growth is about a factor of 1.98 in the data and a factor of 1.82 in the model. Overall, we conclude that our theory can account well for the slow life cycle wage growth of females across the wage distribution.

Table 18: Wage Growth (Age 40/Age 20)

| | Males | | Females | |
|---|---|---|---|---|
| | Data | Model | Data | Model |
| Average | 2.11 | 2.19 | 1.75 | 1.65 |
| Top 50% | 2.33 | 2.44 | 1.98 | 1.82 |
| Bottom 50% | 1.72 | 1.74 | 1.40 | 1.36 |

**The Gender Gap in Wages** We now turn to the implications of the model for the gender gap in wages. Recall that the model is calibrated to match the gender gap in wages at age 20 of 0.18. We find that by age 40 the gender wage gap has increased to 0.39, which implies an increase of 21 percentage points in the gender gap in wages between age 20 and age 40. The increase in the gender wage gap reveals that females spend less effort in accumulating human capital than males. As previously discussed, children, the exogenous differences in hours of work, and the initial differences in human capital are the three channels generating gender differences in the returns to human capital investments in our model. In order to evaluate the quantitative importance of each of these channels, we consider an economy with identical males and females and perform three experiments in which we add one channel at a time until we obtain our benchmark economy. In a first experiment, we assume that females only differ with respect to males in that females give birth to children, which negatively affects their expected labor hours (we refer to this experiment as “only children”). In this economy, children have a negative impact on expected labor supply since mothers are less likely to work and, when employed, work 4% less hours per child than non-mothers. We find that the gender wage gap increases from 0 to 0.08 between ages 20 to 40. Thus, about 40% of the increase in the gender wage gap between ages 20 to 40 (0.08 out of an increase of 0.21) is due to the impact of children on the labor supply of females. The second experiment evaluates, in addition to the impact of children, the consequences of an exogenous reduction in hours of work of 10% for all females. We find that the increase in the gender wage gap between age 20 and age 40 is now 17 percentage points. Since in the first experiment we find that children lead to an increase of 8 percentage points in the gender gap, we conclude that adding the exogenous differences in hours of work further increases the gender wage gap at age 40 in 9 percentage points. The last experiment incorporates all three channels (children, the gender differences in hours worked and, the gender differences in initial human capital), which corresponds to our benchmark economy. Table 19 summarizes the findings of these experiments. We conclude that the impact of children on the labor supply of mothers contributes around 40% to the increase in the gender gap in wages during the life cycle, exogenous gender differences in hours of work contributes another 40% to the increase in the gender gap in wages, while exogenous differences in initial human capital contributes the remaining 20%.

We emphasize that the contribution of children to the increase in the gender gap in wages during the life cycle represents in some sense a lower bound of the overall impact of children on gender differences in wages. The reason is that both the exogenous differences in initial

Table 19: Gender Gap in Wages

| | | | |
|---|---|---|---|
| Benchmark Model: | | | |
| Age 20 | 0.18 | | |
| Age 40 | 0.39 | | |
| $\triangle_{40-20}$ | 0.21 | | |
| | $\triangle_{40-20}$ | Contribution | (%) |
| Counterfactuals: | | | |
| Only Children | 0.08 | 0.08 | 38 |
| + Exo. Hours | 0.17 | 0.09 | 43 |
| + Exo. Initial Human Capital | 0.21 | 0.04 | 19 |

human capital and hours of work between males and females in our model can be in part attributed to the impact of children on employment and hours: The same forces that imply a low employment and hours of females with young children in our model would also induce females to supply less hours of work and less effort in accumulating human capital before age 20.

**Connection to Empirical Literature** Our theory emphasizes the importance of future labor supply as opposed to actual experience for human capital accumulation. Our findings are consistent with the vast empirical literature that finds a substantial gender residual in wage regressions that measure human capital investments by past experience. To illustrate this point, we simulate males and females in our model that are identical in terms of initial human capital and lifetime employment. Our simulated males and females only differ in lifetime labor supply because females work 10% less hours than males and because females expect to have children −with the associated negative impact on labor supply− even though ex-post no female is ever given an opportunity to have children. As a result, we simulate females that are identical to males at age 20 and have identical age-profile of employment over the life cycle. Since females in this experiment work more than 35 hours a week, we follow the empirical literature in counting them as full-time employed. Hence, the data generated by this experiment features no gender differences in experience as measured by full-time employment. The gender wage ratio in this experiment is exactly 1 at age 20 and despite no differences in lifetime full-time employment, at age 40, we nevertheless find a gender wage ratio of 0.91: females earn on average a wage that is 9 percentage points lower relative to the average wage of males. Using this simulated data, a standard wage regression of log wages on experience (measured as full-time employment) and a sex dummy as explanatory variables, would attribute a negative wage effect to being a female worker and a lower return to (measured) experience by females relative to males. This experiment reveals that even females that are highly attached to the labor market, face weaker incentives to invest in human capital than males that can generate sizeable gender wage gaps. Young females spend less effort in accumulating human capital than experience-equivalent males because they anticipate working less hours (even if employed full time). We conclude that, in the context of our model, standard measures of experience typically used in the empirical literature are not good measures of investment in human capital over the life cycle.

**The Family Gap in Wages** Waldfogel (1998) and others have documented a "family gap" in wages, which is calculated as one minus the average wage ratio between women with children and women without children at a given age. The family ratio in wages in our model for females 35 to 40 years of age is 0.902. That is, we find a family wage gap of around

5% per child which is quantitatively consistent with the estimates reported in the empirical literature and with our own calculations using the NLSY79 data. Whereas the literature has attributed this gap to the loss of specific human capital and good job quality matches, in our model the family wage gap arises because career interruptions due to childbirth occur at a stage of the life cycle where the return to human capital investment is relatively high.

**Discussion** The increase in the gender gap in wages between age 20 and age 40 is 21 percentage points in our model, while it is about 14 percentage points in the data. We can think of two possible reasons for this outcome. First, our model assumes that males and females are equally productive at accumulating human capital. Given that the employment rate of women is much lower than that of men, it could well be the case that working women in the data are of higher ability than men, as suggested by some recent evidence from test scores in higher education. A second reason that could explain the slow life-cycle wage growth of females in our model relative to the data is that our theory abstracts from time trends in prices that could have favored relatively more women than men. In fact, Bacolod and Blum (2005) present evidence that in the U.S. economy during the 1968-1990 period the price of cognitive skills has increased while the price of motor skills has decreased. Moreover, they argue that changes in the price of skills have played an important role in the reduction of the gender wage gap during recent decades. Obviously, our results would have shown higher life cycle wage growth of females had we modeled changes in prices that favor females relative to males. Interestingly, the price changes documented by Bacolod and Blum (2005) are likely to benefit more strongly women at the top of the wage distribution than at the bottom since women at the top of the wage distribution are likely endowed with relatively higher levels of cognitive skills.

# 6 Conclusions

We develop a quantitative life-cycle theory of fertility, labor supply, and human capital accumulation decisions that is successful in generating the observed employment ratio, hours of work, duration of non-employment spells, and accumulated experience at age 40 for males. In addition, our model is successful in generating an average fertility rate, birth rates by age, and the impact of children on career interruptions and the labor supply of females as observed in the NLSY data. In our model, fertility implies lower lifetime labor supply, lower returns to investment in human capital, and lower wage growth of females over the life cycle relative to males. We find that fertility accounts for most of the gender differences in labor supply and wages over the life cycle. In addition, the model generates a gender gap in wages across people at different points of the wage distribution as observed in the data.

Our quantitative theory can also be used to study the gender gap in wages within education and racial groups. For instance, Polachek (2004) documents that the gender difference in labor hours is smaller among blacks than whites and that the gender gap in wages appears smaller for blacks than for whites. This evidence is suggestive of the role of human capital accumulation. Our model can also be used to address the substantial decline in the gender gap over the last 20 years in the U.S. data (see Blau and Khan, 1997). Our theory suggests that the factors responsible for the substantial increase in labor hours of women during this period such as the fall in fertility, the increase in part-time work, the availability of child care services, the reallocation of labor within the household, among others; may be important in accounting for the convergence in wages across genders over time. We leave these important research questions for future work.

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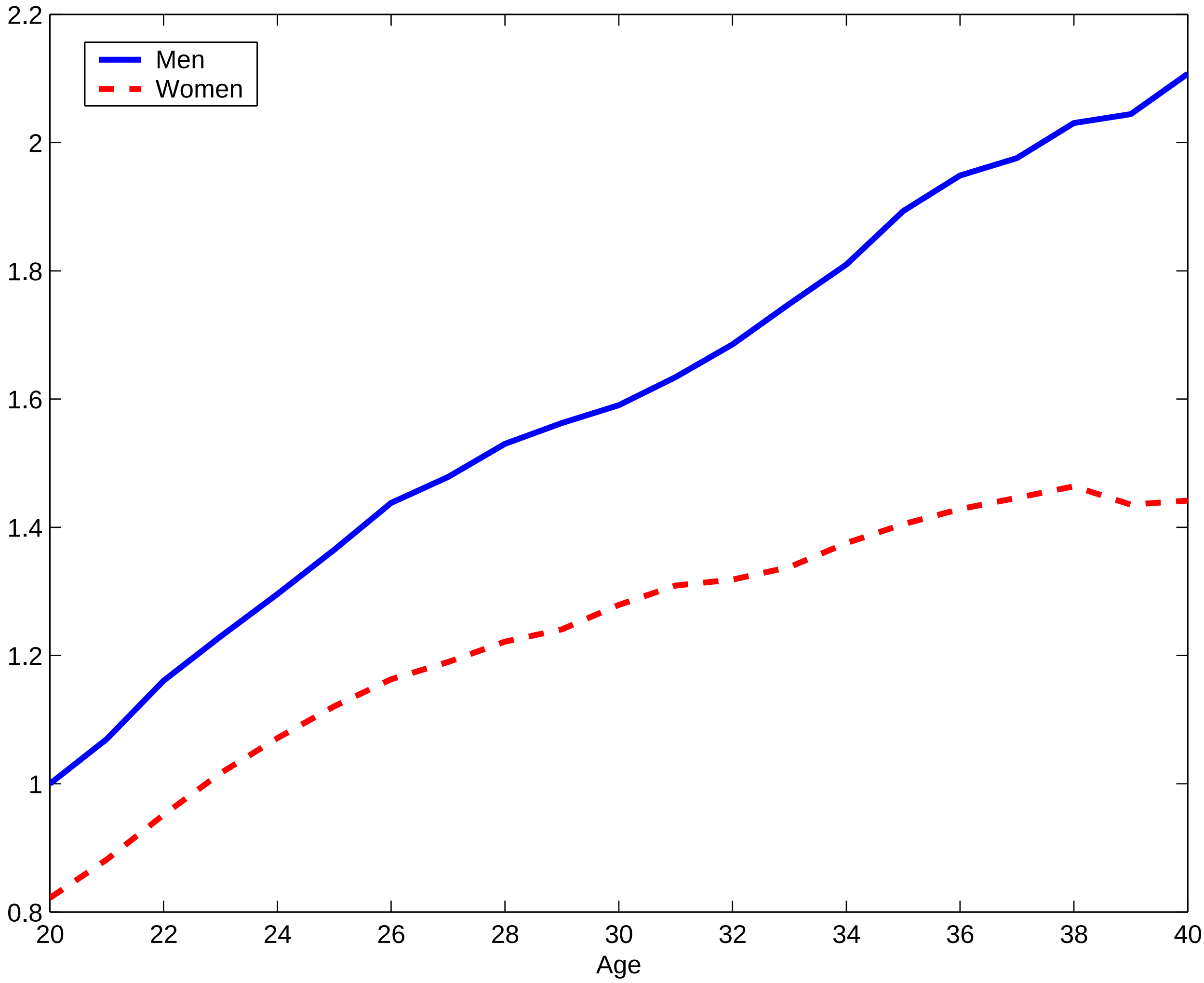
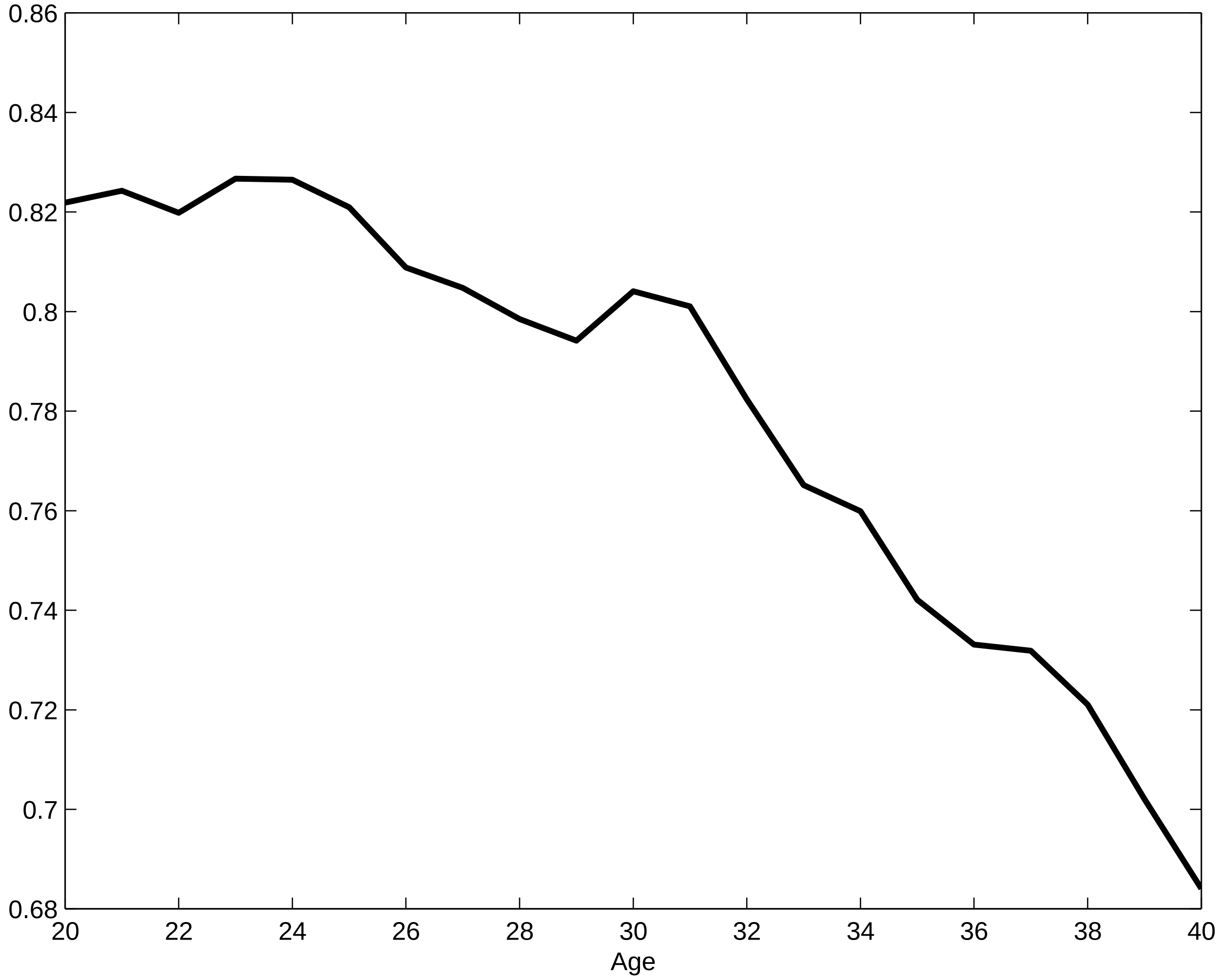
Figure 1: Average Hourly Wage by Age



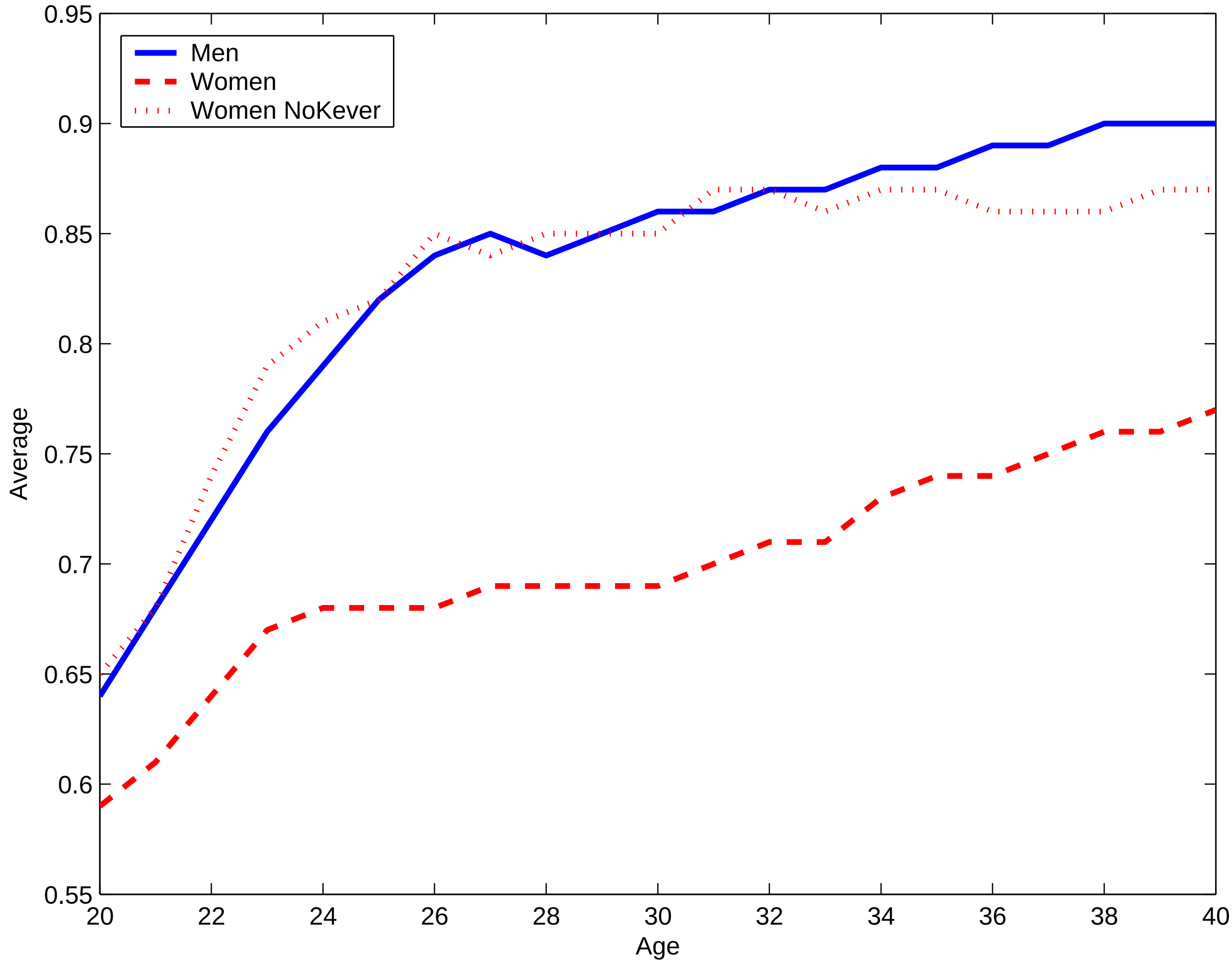

Relative to the average wage of men at age 20.

Figure 2: Gender Wage Ratio by Age



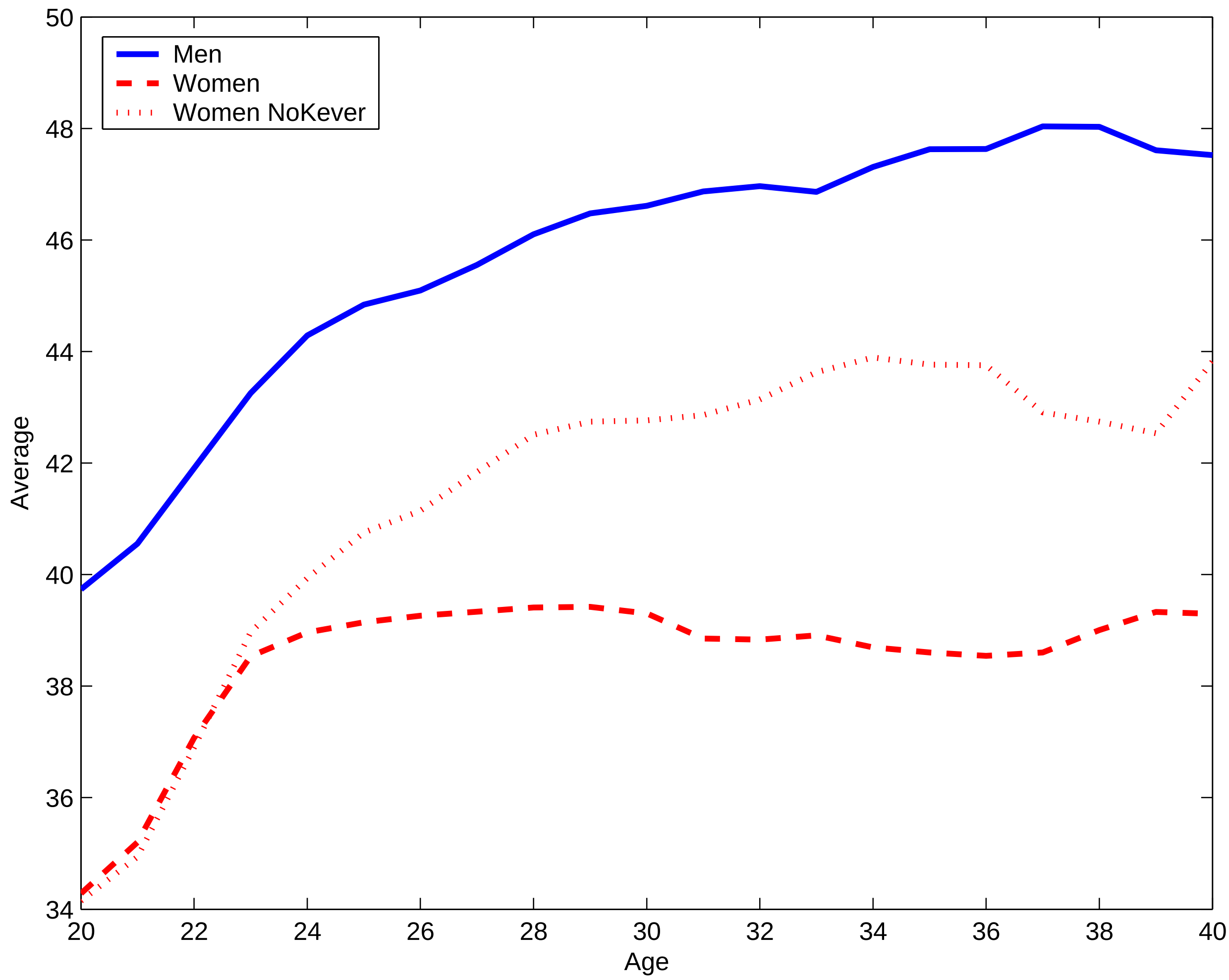

Average wage of women relative to males at each age.

Figure 3: 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 4: 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 5: Employment Ratio by Age - Males

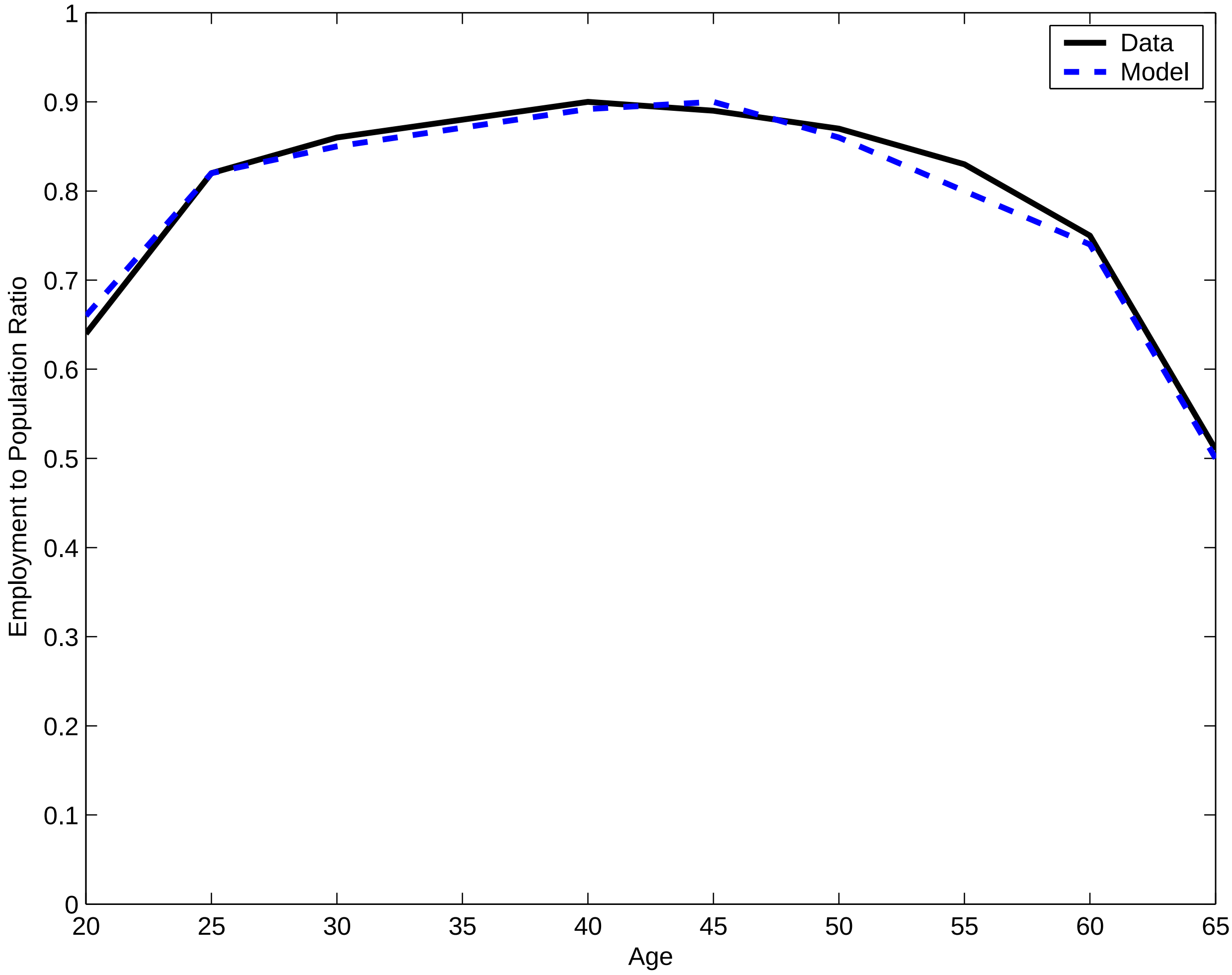


Figure 6: Age Profile of Wages - Males

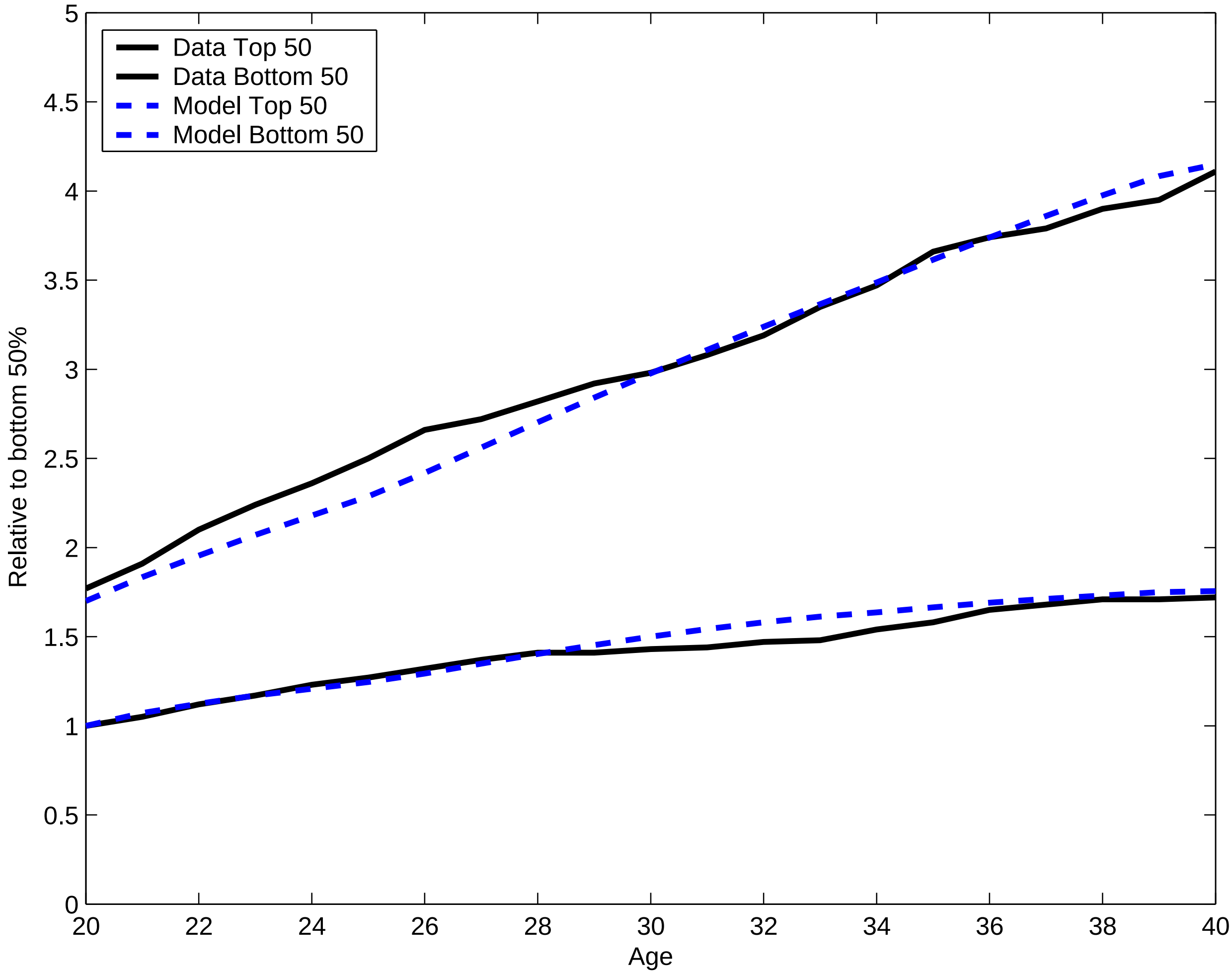


Figure 7: Experience Profile of Wages - Males

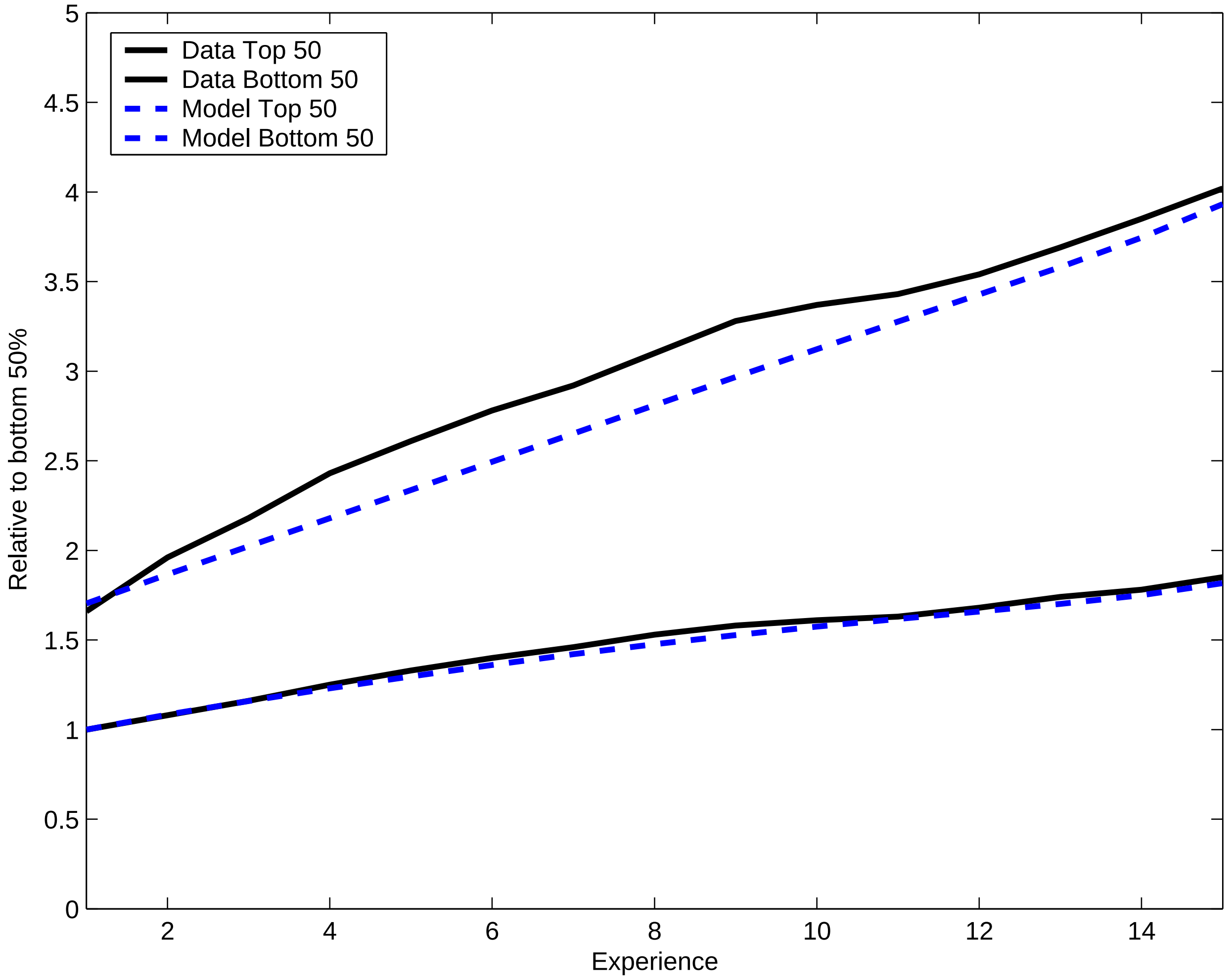
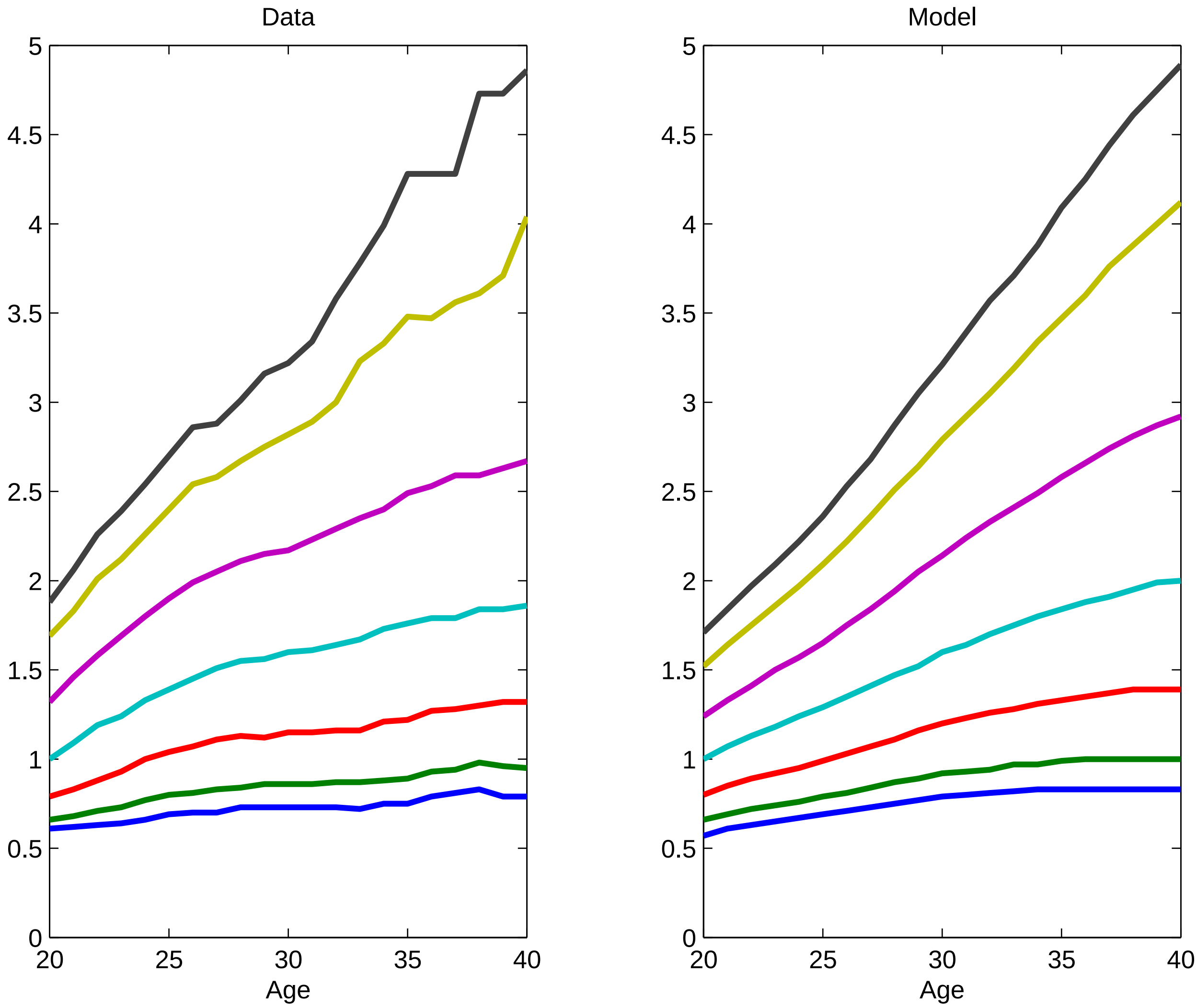
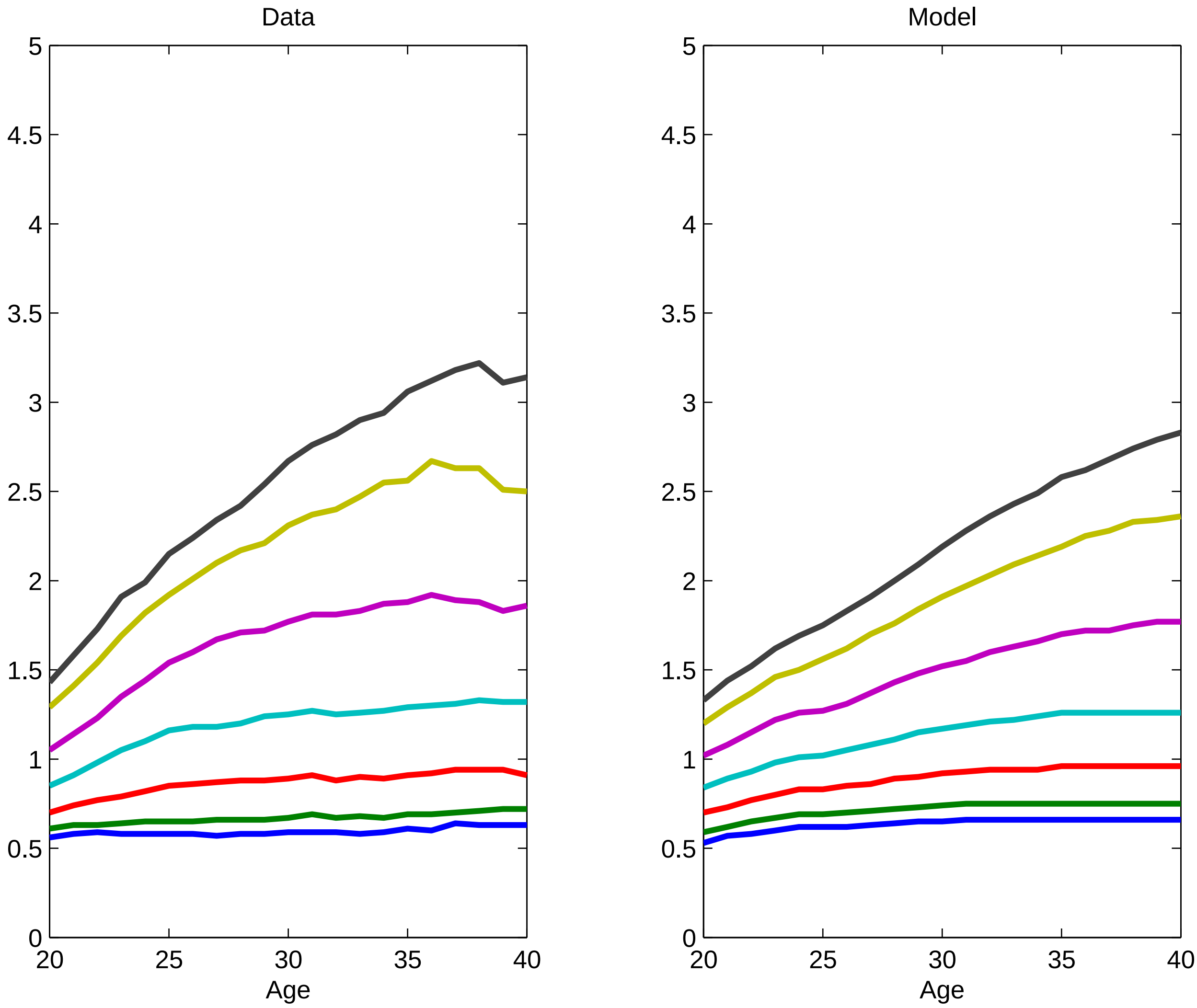


Figure 8: Age Profile of Wages - Males




The lines correspond to the following percentiles of the distribution of wages: 5, 10, 25, 50, 75, 90, and 95. Relative to the median wage of males at age 20.

Figure 9: Age Profile of Wages - Females




The lines correspond to the following percentiles of the distribution of wages: 5, 10, 25, 50, 75, 90, and 95. Relative to the median wage of males at age 20.