USC FBE MACROECONOMICS AND INTERNATIONAL FINANCE WORKSHOP
presented by Luisa Fuster
FRIDAY, March 4, 2005
3:30 pm – 5:00 pm, **Room: HOH-601K**

A Quantitative Theory of the Gender Gap in Wages†

Andrés Erosa

University of Toronto

Luisa Fuster

University of Toronto

Diego Restuccia

University of Toronto

March 2005

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 labor supply of women. In this paper, we asses the role of gender differences in life-cycle labor supply on the gender wage gap and its increase over the life cycle in the context of a model with (unobserved) human capital accumulation. In our model, lower lifetime intensity of market activity reduces the incentives for human capital accumulation. We calibrate the model to panel data of men and to fertility and child related labor market histories of women. We find that gender differences in labor hours account for the increase in the gender gap in wages during the life cycle and the family gap in wages documented in the NLSY data.

Keywords: Gender gap, employment, experience, fertility, unmeasured human capital.
JEL Classification: J2,J3.

†We are grateful to Ig Horstmann and Richard Rogerson for comments and suggestions. We also thank the comments of Aloysius Siow, Marcelo Veracierto, and seminar participants at the 2004 SED in Florence, Arizona State University, the Federal Reserve Bank of Richmond, the University of Pittsburgh, and the University of Guelph. We thank Chirstine Neill for invaluable research assistance. All remaining errors are our own. We acknowledge the financial support of the BBVA foundation. Restuccia acknowledges the support from the Connaught Fund and the Institute for Policy Analysis at the University of Toronto and the Social Sciences and Humanities Research Council of Canada. *Contact Information:* andres.erosa@utoronto.ca; luisa.fuster@utoronto.ca; and diego.restuccia@utoronto.ca.

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. A large empirical literature is aimed at understanding the sources of gender differences in wages. Empirical studies typically find that men earn higher wages (even after controlling for gender differences in observed characteristics) and face higher returns to labor market experience than women. One problem in interpreting these results is that we can not assess to what extent they are driven by differential (unobserved) investment in human capital. Economic theory suggests that this is not an easy problem to circumvent. Since the return to human capital accumulation depends on future labor supply, theory implies that investment in human capital should be driven by expected labor supply (rather than by past labor supply). While theory prescribes that investment decisions are forward looking, obvious data limitations makes it hard to incorporate labor-supply expectations into the empirical analysis.

In this paper we use quantitative theory in order to assess the importance of (unmeasured) investment in human capital in understanding gender differences in wages. To this end, we build a quantitative life-cycle theory of human capital accumulation and labor supply decisions. In our theory, people decide how much (unobserved) effort to spend in accumulating human capital on the job and whether to work or stay at home. We assume that females also make fertility decisions which, in turn, may negatively affect their expected labor supply. Because we assume that there are no gender differences in the human capital technology, we use panel data on males (regarding wages and labor supply) to calibrate the human capital technology. We then use our quantitative theory to measure investment in human capital by females. In particular, we assess the importance of gender differences in (expected) labor supply for gender differences in wage growth. Moreover, we use our theory to measure the impact of children on female wages and on the wage of mothers relative to non-mothers.

Our approach is motivated by some basic insights from human capital theory as well as by some observations that we document using panel data − the 1979 cohort of the National Longitudinal Survey of Youth (NLSY79). Our starting point is that there are substantial gender differences in labor supply. 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 translate into a stock of accumulated experience that is about 50% larger for men than for women. We emphasize that gender differences in cumulative hours of work are much larger than the ones obtained by focusing on years of employment, which is the measure of experience typically used in empirical studies.[1] 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 women face lower wage growth than men during the life cycle. Using the NLSY79, we document that

[1] An advantage of the NLSY, relative to other data sources such as CPS or PSID, is that it provides week by week data on hours of work. This is important because we find large gender differences in hours of work, even among full-time workers.

the gender gap in wages almost doubles from age 20 to age 40 − from about 18% points at age 20 to 32% 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 modelling human capital investments 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. To illustrate these ideas consider a hypothetical path of hours of work for a representative male and a representative female as described in Figure 1, Panel A. Up to age 30 these two people are identical from the point of view of labor market attachment and therefore, any observed difference in wages at this age may seem puzzling. Instead, in the context of a human capital model, investment in unmeasured human capital occurs between the ages of 20 and 30. The incentive for human capital accumulation depends on the intensity to which human capital is utilized in the future, therefore, given the assumed life-cycle path in hours for males and females in Panel A, females would invest less in human capital than males, and a portion of any difference in wages at age 30 may be attributed to differential (unmeasured) human capital accumulation. The life-cycle path for hours may be more complicated than depicted in Panel A, females may follow very different paths for labor hours, perhaps associated with the impact of children on labor supply, as illustrated in Panel B. To the extent that young females may not know the exact path of future labor supply, investment in unmeasured human capital may depend on the expected life-time labor supply and therefore, there may be differential investment in human capital even if ex-post, the path for employment is similar between a male and a female. The uncertainty in hours of work related to future fertility implies gender differences in human capital investment and wages even among females and males that ex-post have similar life-cycle paths of employment. Indeed, and contrary to the empirical literature on gender differences in wages, from the viewpoint of a human capital model, the returns to human capital accumulation depend on (expected) life-time labor supply, not just actual experience.

We calibrate our 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 males. Regarding females, our model replicates the birth rates by age and the impact of children on career interruptions and labor supply. We find that gender differences in employment and hours 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% 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 is due to the impact of children on female labor supply 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 labor supply at a stage of the life cycle when the returns to (unmeasured) human capital accumulation are high. Our results also emphasize the importance of future (expected life time) labor supply for human capital accumulation as opposed to actual experience. We find that about 40% of the gender gap in wages can be attributed to lower expected labor hours of females relative to males. In one experiment, we simulate females that start their working life with the same human capital as males and that behave as males in terms of employment decisions (we assume that females do not have the opportunity to give birth). Even though the data generated by this experiment involves males and females with the same employment history, we find that females spend less effort in accumulating human capital. As a result, by age 40 these females have on average 9% less human capital than males. We view this result as questioning the use of actual experience measures in statistical decomposition analysis of the gender gap in wages.

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 et. al. (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 intertemporal elasticity of substitution of labor supply rather than gender differences in wages. Attanasio et. al. (2004) and Greenwood, et. al. (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.[2]

Our paper also relates to the literature on wage differences between mothers and nonmothers (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 with unmeasured human capital, the family gap in wages arises because children generate career interruptions at a stage of the life cycle where substantial investment in unmeasured human capital occur.

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 section 4 discusses the calibration. Section 5 presents the main quantitative results and

[2]More generally, our paper follows a recent tradition in quantitative theory on the economics of the family initiated by Aiyagari et. al. (2000) and Regalia and Ríos-Rull (1998).

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 show that men work much more over the early part of their life-cycle than women and that the origins of these gender differences in labor supply can be traced to the impact of children in labor market decisions of women.

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 the sample are 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 2 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, that is, the gender gap in wages increases by 14 percentage points over the early part of the life cycle. (See Figure 3.)[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

[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.

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]

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 4 and 5 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

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

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

where H is aggregate labor hours, P is population, and W is employment. In average, men work 40% more hours than women, while among those working, men work almost 20% more hours than women.

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.

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. Table 3 reports statistics of non-employment spells for men and women. 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, whereas the average duration of a non-employment spell for women is 65 weeks, that is, non-employment spells last an average six months longer for women than for men.[5] Table 4 reports the duration distribution of

[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

non-employment spells for men and women. Compared to non-employment spells of 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.

Table 3: Summary Statistics of Non-Employment Spells

	Men	Women
Average number of spells	2.9	3.1
(std)	(2.5)	(2.5)
Number distribution (percentage):		
0-2	55	50
3-4	23	26
>4	22	24
Average length in weeks	41	65
(std)	(71)	(110)
Average length in weeks by:		
Childbirth†	-	104 (125)
No childbirth	-	44 (67)

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 one or more children.

The Accumulation of Experience Women are characterized by lower employment, fewer hours of work, and longer spells of non-employment than men. These gender differences in labor supply imply that on average, women accumulate less experience in the labor market than men. Table 5 documents the average accumulated experience for men and women at age 40 in our panel data, for two types of measures of experience: Accu-

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 4: Duration Distribution of Non-Employment Spells (%)

	Men	Women	Women	
Duration (weeks):			No childbirth	Childbirth†
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 1 child at the start or during the spell.

mulated weeks of work and accumulated hours of work.[6] Table 5 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 5 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).

Children and Labor Market Outcomes Labor supply differences across gender are substantial and by age 40 men have accumulated much more experience in the labor market than women. What is striking in comparing labor market outcomes of men and women is the role played by the presence of children 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.

[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 5 assume these cases as zero hours, but alternative assumptions yield similar results.

Table 5: 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 per week of work.

For the last observation of every woman in our sample − when they are between 36 to 43 years of age − we consider women that had not had children up to that point and we refer to them as women with no children (Women NoKever in the graphs). 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 4. 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 5. Comparing the distribution of hours of work between men and women without children reveals the same pattern reported in Figures 4 and 5 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.

Children have lasting effects on employment and hours of women. Table 6 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.

In order to characterize the impact of children in the duration of non-employment spells of women reported in Tables 3 and 4, 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). We find that an important fraction of all non-employment spells do not involve the birth of a child (almost 82%). The average duration of "No Childbirth" non-employment spells of women is similar to that of men, 44 weeks. The main difference in the duration of non-

Table 6: Average Hours and Employment

	Hours/Person		Hours/Worker		Employment Ratio	
Men	37.6		45.6		82.6	
Women	26.7		38.5		69.5	
By No. of Children:						
	Under 18	Under 6	Under 18	Under 6	Under 18	Under 6
0	32.5	31.1	40.0	39.6	81.2	78.3
1	25.0	21.7	38.1	36.3	65.3	59.5
2	23.1	16.0	36.7	34.3	62.8	46.4
3 or more	18.6	11.3	35.8	34.1	51.8	32.8
By Age of Youngest Child:						
Less than 3 mo.	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	
6 to 7 years	25.5		37.4		68.2	

employment spells between men and women is in the duration of non-employment spells of women involving the birth of a child: The average duration of "Childbirth" non-employment spells is 104 weeks. The duration distribution of non-employment spells of men and women of "No Childbirth" is similar: 63-66% of the spells last less than 2 quarters and 81-84% last less than a year, whereas for the "Childbirth" non-employment spells of women 30% last less than 2 quarters and 50% last more than a year.

A large portion of the gender differences in accumulated experience can be traced to the effect of children in labor supply of women. Table 5 documents accumulated experience for women with and without children. Women with no children accumulate about the same amount of experience than men: About 97% of the labor experience of men measured in weeks and 89% of the labor experience measured in hours. Instead, men accumulate 27%

and 57% more experience than women with children in weeks and hours.

Labor Market Decisions around Childbirth Our theory focuses on the impact of children on labor market decisions of women. The NLSY79 provides the information necessary to characterize labor market decisions of women around the event of a childbirth.[7] In our sample, 56% of women around the event of a childbirth are employed, while the remaining 44% are non-employed.

For the group of women that are employed around childbirth, 57% remain employed and 3% never return to work. Table 7 reports the complete distribution of spells for employed mothers around childbirth. A large portion of employed mothers around childbirth have non-employment spells of short duration: 21% return to work within a quarter. But a substantial fraction of employed mothers return to work after one year (12%). Without mothers that have not returned to work (never returned), the mean duration of non-employment spells for employed mothers is about one year (55 weeks with a standard deviation of 92 weeks).

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

[7]We focus on childbirth of women 20 years or older and with information about their labor market status. For each childbirth, the NLSY79 documents the number of weeks left (returned) employment before (after) childbirth. Because some women leave the employment state some weeks before childbirth, we consider as employed all women that left the employment state within 6 weeks or less of childbirth. We abstract from spells of non-employment of short duration (6 weeks or less).

Table 7: Distribution of Non-Employment Spells for Mothers around Childbirth (%)

Duration (weeks):	Spell around Childbirth (Employed)	Birth During Spell (Non-employed)
No Spell (≤ 6)	57	-
1 quarter (7-19)	21	20
2 quarters (20-32)	5	10
3 quarters (33-45)	3	9
4 quarters (46-58)	3	7
More than a year (>58)	12	54
Never returned	3	20

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 modelling 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.

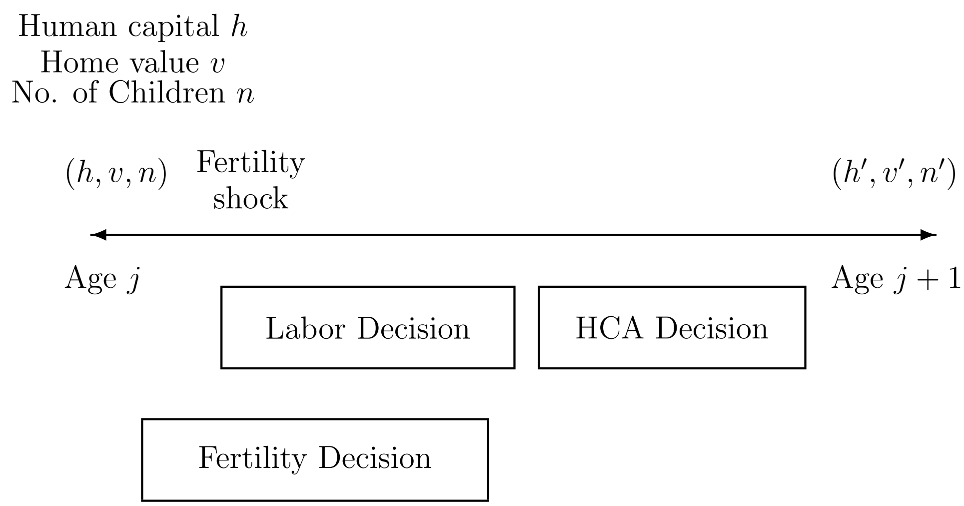
Labor Decision We model the labor participation decision by assuming that people draw a stochastic value of staying at home, which could be correlated over time and vary with age and, in the case of females, with the number of children. People decide whether to work a fixed amount of hours (that depends 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 (unmeasured) 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.[8] 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 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.

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

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 that 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, people working decide how much effort to exert in accumulating human capital. People that do not work during the current period, enjoy the value of staying at home. At the end of the period, people 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,

$$\begin{aligned} W^j(h,n,v) &= hl(j,n) + (1-l(j,n))u(h,v) + \gamma_n \log(1+n) \\ &\quad + \max_{e\in[0,1]} \left\{c(j,h)\log(1-e) + e\hat{V}^i(h(1+\triangle),n,v) + (1-e)\hat{V}^i(h,n,v)\right\}, \end{aligned}$$

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 γ_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 that 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 males, 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. 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 employment and hours histories of women after child-birth. 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 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 and Table 8 presents a summary of parameters and targets.

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 male employment rate 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 (ρ, σ_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 $\triangle$, γ_h, and the parameters (α_1, α_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 8: Calibration for Males

Parameter	Target
v_j	Employment by age
ρ	Duration of non-employment spells
σ_{ϵ_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 (ρ, σ_ϵ), 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 in Table 10.

4.2 Calibration for Females

Preference for Children and Fertility Opportunities 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 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 parameters and targets in the data is reported in Table 9 and of parameters and the resulting values in the calibration in Table 10.

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 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 can not quit their jobs to enjoy v_c. For computational simplicity, we assume that v_c is drawn from an exponential distribution with mean μ_{v_c}. The parameter μ_{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 women work in average 10% less hours than males (at every age) and that in average each child reduces the hours of work for females 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 women of age 20 observe wages that are in average 18% lower than males. 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, work less hours than males. Females would face lower incentives than males to invest in market human capital not only after age 20, as emphasized in our theory, but also prior to age 20.

Table 9: Calibration for Females

Parameter	Target
$\theta^j(n)$	Distribution of number of children
γ_n	Total fertility rate
μ_{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 γ_n, and the parameter describing the distribution for the value of staying at home with children μ_{v_c}. As discussed for the 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 10: Parameter Values

Parameter	Value	Parameter	Value
v_{20}	2.40	$\triangle$	3%
v_{25}	0.41	α_1	0.35
v_{30}	0.36	α_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	$\theta^j(2)$	$\theta^j(0) * 0.85$
ρ	0.76	$\theta^j(3+)$	$\theta^j(0) * 0.60$
σ_ϵ	0.79	μ_{v_c}	3.2
$\sigma_{h_{20}}$	0.33	γ_n	1.0
γ_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 6 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 11).

Table 11: Distribution of Accumulated Experience at age 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

Figures 7 and 8 document the age and experience profile of wages for the model and the data for the average of people in the bottom and top 50% of the age and experience distribution of wages. The model captures well the heterogeneity and 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 9). Another target in our calibration procedure is the duration distribution of non-employment spells for men. Table 12 reports the duration distribution of these spells in the model and in the data.

Table 12: 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 13 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 14 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 15 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 13: 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
$\geq$4	9.7	7.6

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 impact on expected employment and working hours (young working mothers − 40 year 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

Table 14: 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 15: 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

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 is yes.

Female labor supply As discussed in the calibration section, the model is calibrated to panel data of males and only to data of women that relates directly to the number of children and their impact in employment and hours of work after childbirth. We emphasize that our calibration did not target the gender differences in labor supply. Table 16 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 low female employment relative to males (such as, household specialization). In addition, the model implies slightly shorter duration of female non-employment spells than in the data (see Table 17). 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 16: 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 17: 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

Table 18: 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

Female Wages in the Life Cycle Our model of human capital investments can account for the low female wage growth in the life-cycle relative to males. In fact, if anything, we find that in our model female wages grow with age slightly less than in the data. While in the data female wages grow between ages 20 to 40 by a factor of 1.75, in our benchmark economy female wages 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 10). 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 than in the data. In Table 19, we show that wage growth for the bottom 50% of the wage distribution is given by a factor of 1.40 in the data and 1.36 in the model. Regarding the top 50% of the wage distribution, wage growth is about 1.98 in the data and 1.82 in the model. Overall, we conclude that our theory can account well for the slow wage growth of females during the life cycle across the wage distribution.

Table 19: 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% points in the gender gap in wages between age 20 to 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, exogenous differences in hours of work, and initial differences in human capital are three channels generating gender differences in the returns to human capital investments. 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 males in that they give birth to children, which negatively impact on 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 than non-mothers and, if they work, they work 4% less per child. 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 female labor supply. 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 women. We find that the increase in the gender wage gap between age 20 to age 40 is now 17% points. Since in the first experiment we find that children lead to an increase of 8% in the gender gap, we conclude that adding exogenous hours further increases the gender wage gap at age 40 in 9% points. The last experiment incorporates all three channels (children and gender differences in exogenous hours and initial human capital), which corresponds to our benchmark economy.

Table 20 summarizes the findings from these experiments. We conclude that the impact of children on 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%.

Table 20: 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
No Children Ever	0.09	0.09	43

We emphasize that the contribution of children to the increase in the gender gap in wages during the life cycle represent 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 human capital and hours of work between males and females in our model can be in part attributed to the impact of children in employment and hours: The same forces that imply lower employment and hours for 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.

No Children Ever Our theory emphasizes the importance of future (expected life-time) labor supply for human capital accumulation as opposed to actual experience. To illustrate the importance of this factor to the increase in the gender gap in wages in our model, we solve the model without initial gender differences in human capital. Moreover, we simulate a large number of females that make employment decisions based on the policy rule of males and that they do not draw a fertility opportunity (although in constructing expectations, having children is as likely during the life-cycle as in the benchmark economy). As a result, we simulate females that are equal 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 (and thus neglecting that they actually work 10% less than males). The data generated by this experiment, hence, do not feature gender differences in experience, as measured by weeks of full time employment. We nevertheless find that the simulated females earn on average a wage that is 9% points lower relative to the average wage of males. The simulation reveals that even females that are highly attached to the labor market, face weaker incentives to invest in human capital than males. Young females spend less effort in accumulating human capital than experience-equivalent males because they expect to have children and to work less hours (even if employed full time). Its interesting that a standard wage regression with weeks of full time employment and a sex dummy as explanatory variables, would attribute a negative wage effect to being a female worker and lower return to (measured) experience by female workers relative to male workers.

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 (or age range). 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 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 capital and good job quality matches, in our model the family 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% points in our model, while it is about 14% points in the data. We can think of two possible reasons for this outcome. First, our model assumes that male 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 males, as suggested by some recent evidence from test scores in higher education. A second reason that could explain the slow female wage growth 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 males. In fact, Bacolod and Blum (2005) present evidence that in the U.S. economy during the 1968-1990 period the price of cognitive skills have increased while the price of motor skills have 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 female wage growth had we modelled 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

Our quantitative theory of the gender gap in wages is successful in matching the employment ratio, hours of work, duration of non-employment spells, and accumulated experience at age 40 for males. In addition, our theory is successful in generating an average fertility rate, birth rates by age, and the impact of children on career interruptions and labor supply of females. Our theory of (unmeasured) investment in human capital implies that gender differences in employment and hours lead to differential returns to experience across genders and a gender gap in wages that increases with age. The model generates a gender gap in wages across people at different points of the distribution of wages. In addition, our model implies a family gap in wages and gap in wages between females without children and males. Our model generates a family gap in wages because the impact of childbirth on labor supply of mothers occurs at a stage of the life cycle where the returns to (unmeasured) human capital accumulation are relatively high.

Our theory of differential investment in human capital can 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 last 20 years in the U.S. data (see Blau and Khan, 1997). Our theory suggest 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.

References

[1] Aiyagari, S. Rao, Jeremy Greenwood, and Nezih Guner (2000). “The State of the Union,” *Journal of Political Economy* **108**(2), 213-44.

[2] Anderson, Deborah, Melissa Binder, and Kate Krause (2002). “The Motherhood Wage Penalty: Which Mothers Pay It and Why?” *American Economic Review*, 92(2), May, 354-58.

[3] Attanasio, O., Low, H., and Sanchez-Marcos, V. (2004). ”Explaining Changes in Female Labour Supply in a Life-cycle Model.” Manuscript. University College London.

[4] Avolio, Bruce J. and David A. Waldman, 1994, “Variations in Cognitive, Perceptual, and Psychomotor Abilities across the Working Life Span: Examining the Effects of Race, Sex, Experience, Education, and Occupational Type,” *Psichology and Aging*, 9(3): 430-442.

[5] Bacolod, M. and Blum, B. (2005). ”Two Sides of the Same Coin: U.S. ”Residual” Inequality and the Gender Gap.” Manuscript. University of Toronto.

[6] Blau, F. and Kahn, L. (1997). ”Swimming Upstream: Trends in the Gender Wage Differential in the 1980’s,” *Journal of Labor Economics* **15**, 1-42.

[7] Blau, F. and Kahn, L. (2000). “Gender differences in Pay,” *Journal of Economic Perspectives* **14**, 75-99.

[8] Bowlus, A. (1997). “A Search Interpretation of Male-Female Wage Differentials,” *Journal of Labor Economics* **15**, 625-57.

[9] Da-Rocha, J.M. and Fuster, L. (2004). “Why Are Female Participation and Fertility Rates Positively Correlated across OECD Countries? ,” Manuscript. University of Toronto.

[10] Erosa, A., L. Fuster, and D. Restuccia (2001). “A General Equilibrium Analysis of Parental Leave Policies.” Manuscript, University of Toronto.

[11] Erosa, A. L. Fuster, and D. Restuccia (2002). “Fertility Decisions and Gender Differences in Labor Turover, Employment, and Wages.” *Review of Economic Dynamics* 5(4): 1354-78.

[12] Greenwood, J., Seshardi, A., and Yorukoglu, M. (2005). “Engines of Liberation.” *Review of Economic Studies* 72: 109-33.

[13] Huggett, M., Ventura, G., and Yaron, A. (2004). ”Human Capital and Earnings Distribution Dynamics,” forthcoming *Journal of Monetary Economics*.

[14] Imai, S. and M. Keane (2004). “Intertemporal Labor Supply and Human Capital Accumulation.” *International Economic Review* 45(2): 601-42.

[15] Jones, L., Manuelli, R. and McGrattan, E. (2003). “Why Are Marrierd Women Working so Much?” Staff Report 317, Federal Reserve Bank of Minneapolis.

[16] Olivetti, Claudia (2001). “Changes in Women’s Hours of Market Work: The Effect of Changing Returns to Experience.” Manuscript. Boston University.

[17] O’Neill, June (2003). “The Gender Gap in Wages, circa 2000” *American Economic Review Papers and Proceedings* 93(2): 309-25.

[18] Polachek, Solomon (2004). “How the Human Capital Model Explains Why the Gender Wage Gap Narrowed.” Discussion Paper No. 1102, IZA.

[19] Regalia, F. and Rios-Rull, V. (1998). ”What Accounts for the Increase in the Number of Single Households,” Manuscript, University of Pennsylvania.

[20] Skirbekk, Vegard, 2003, “Age and Individual Productivity: A Literature Survey,” Max-Planck Institute for Demographic Research.

[21] Waldfogel, J. (1998). ”Understanding the ”Family Gap” in Pay for Women with Children,” *Journal of Economic Perspectives* **12**, 137-56.

[22] Wood, R., Corcoran, M., and Courant, P. (1993). "Pay Differences among the Highly Paid: The Male-Female Earnings Gap in Lawyers' Salaries," *Journal of Labor Economics* **11**, 417-41.

Figure 1: Illustration

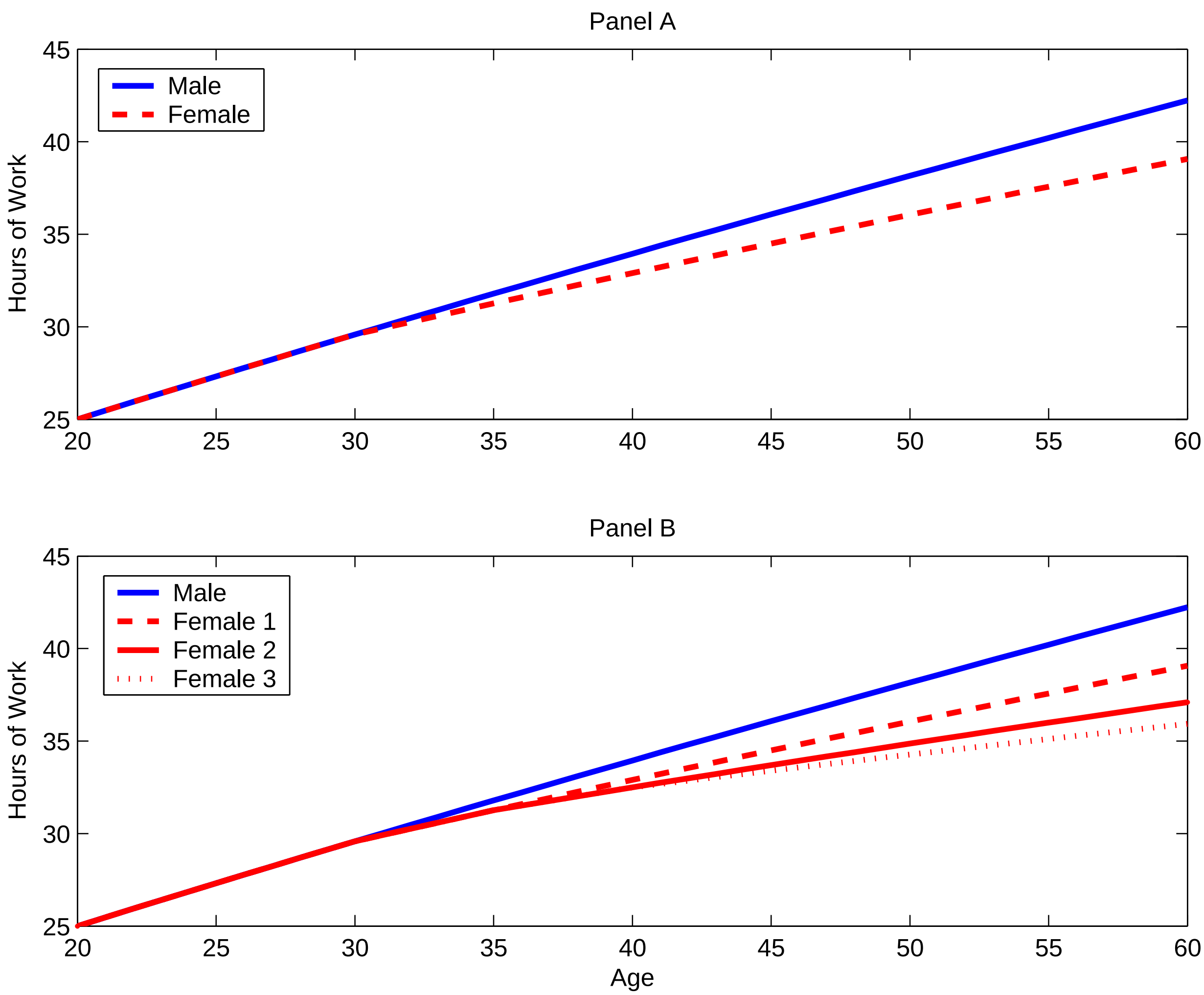
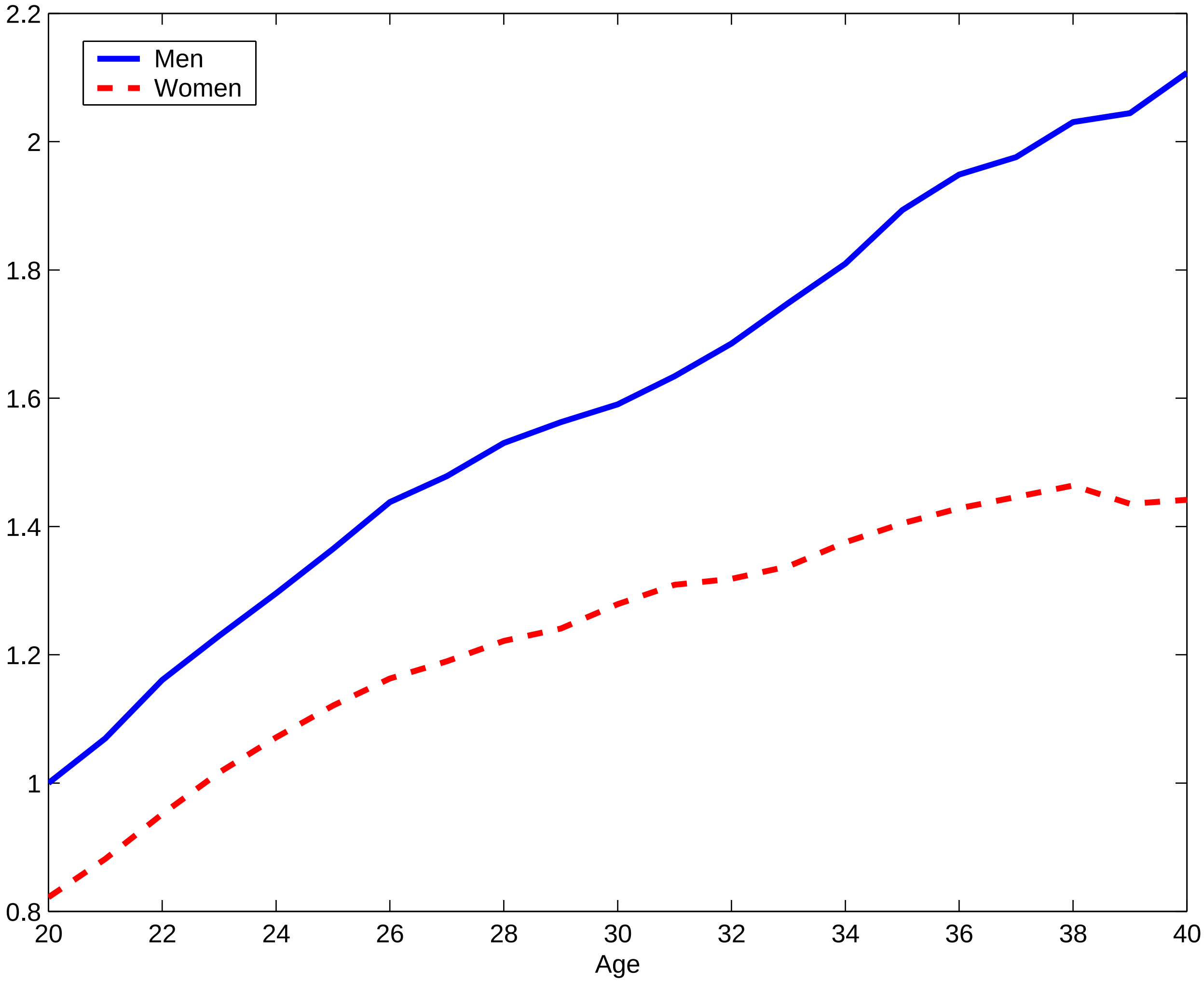
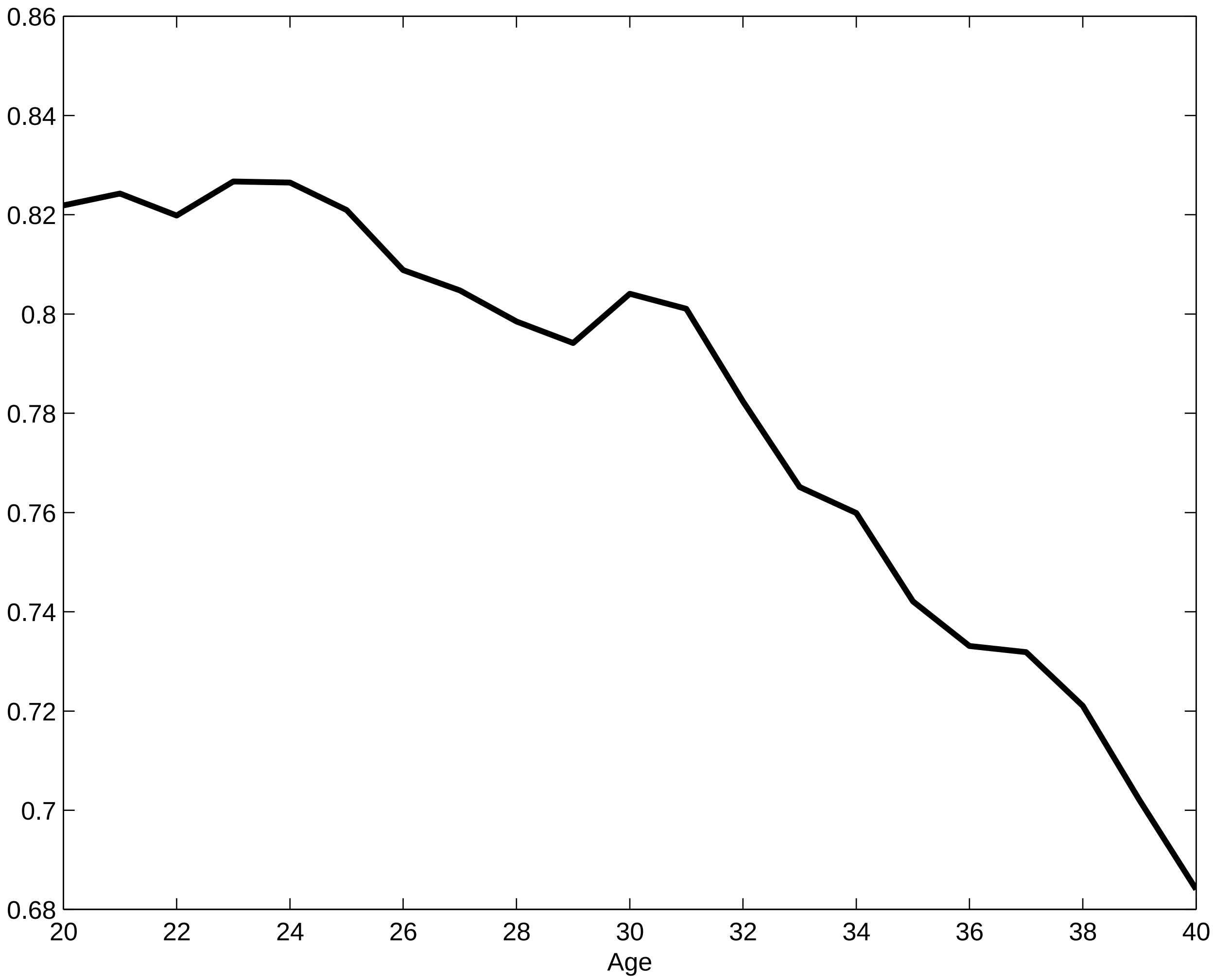


Figure 2: Average Hourly Wage by Age



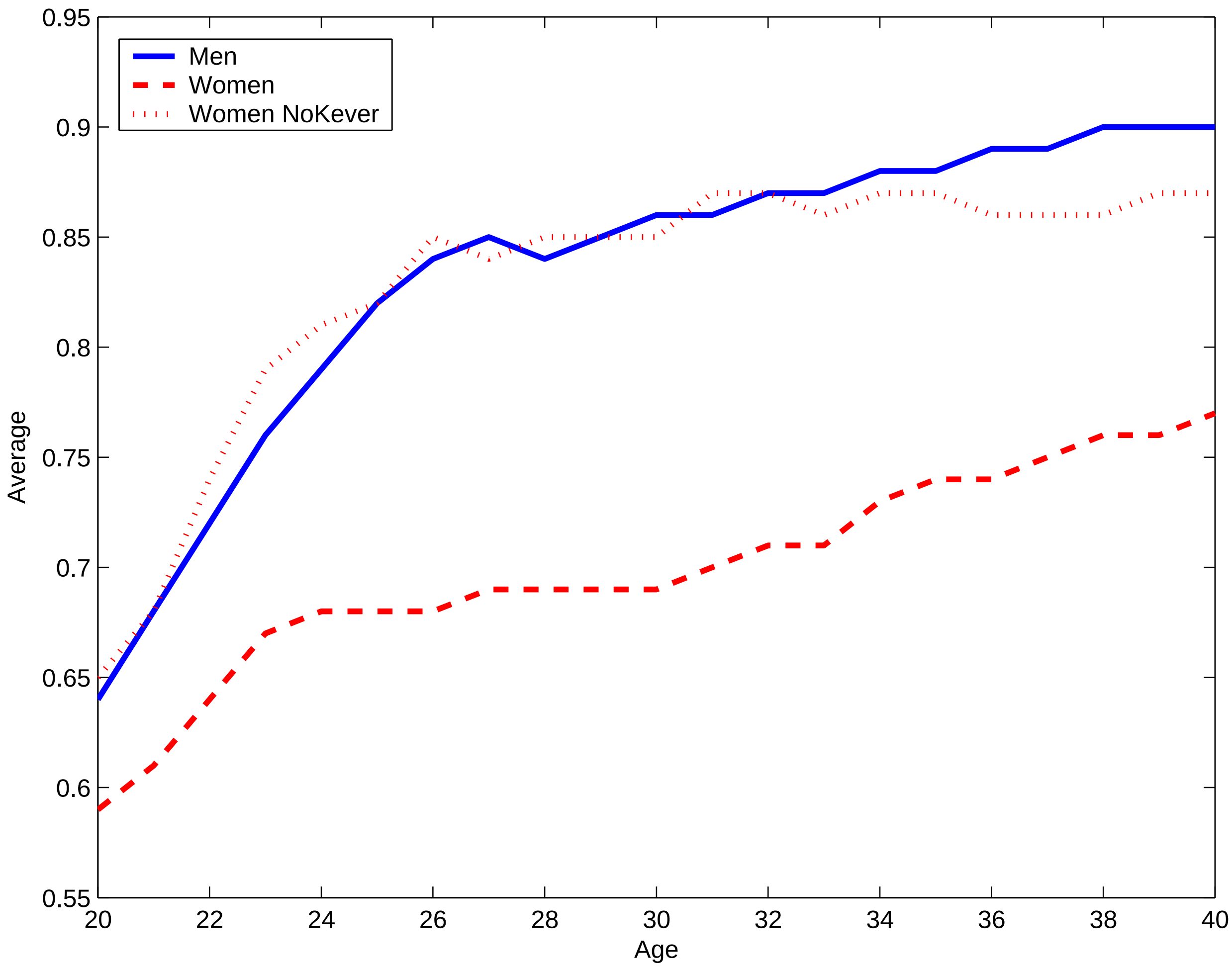
Relative to the average wage of men at age 20.

Figure 3: Gender Wage Ratio by Age



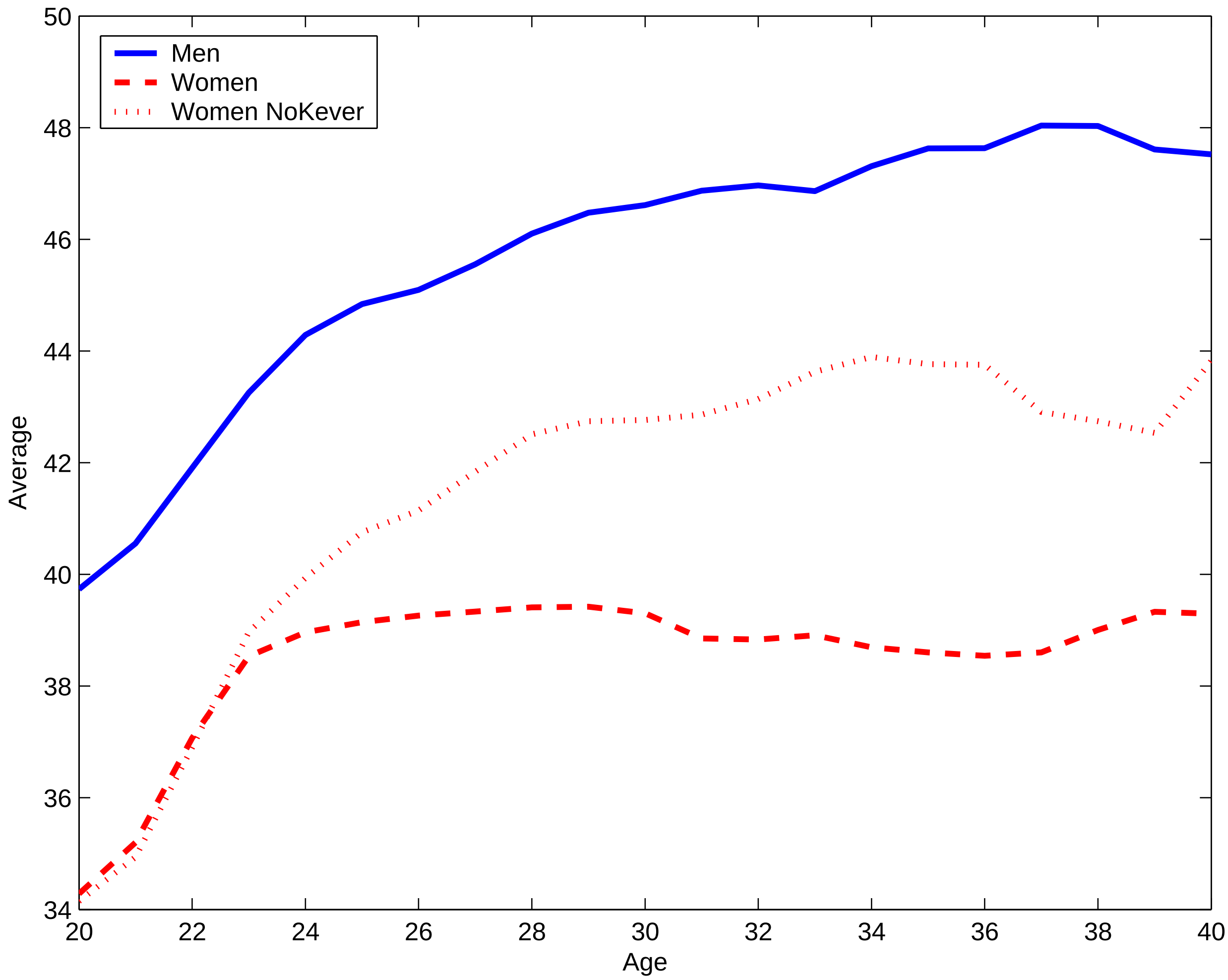
Average wage of women relative to males at each age.

Figure 4: 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 5: 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 6: Employment Ratio by Age - Males

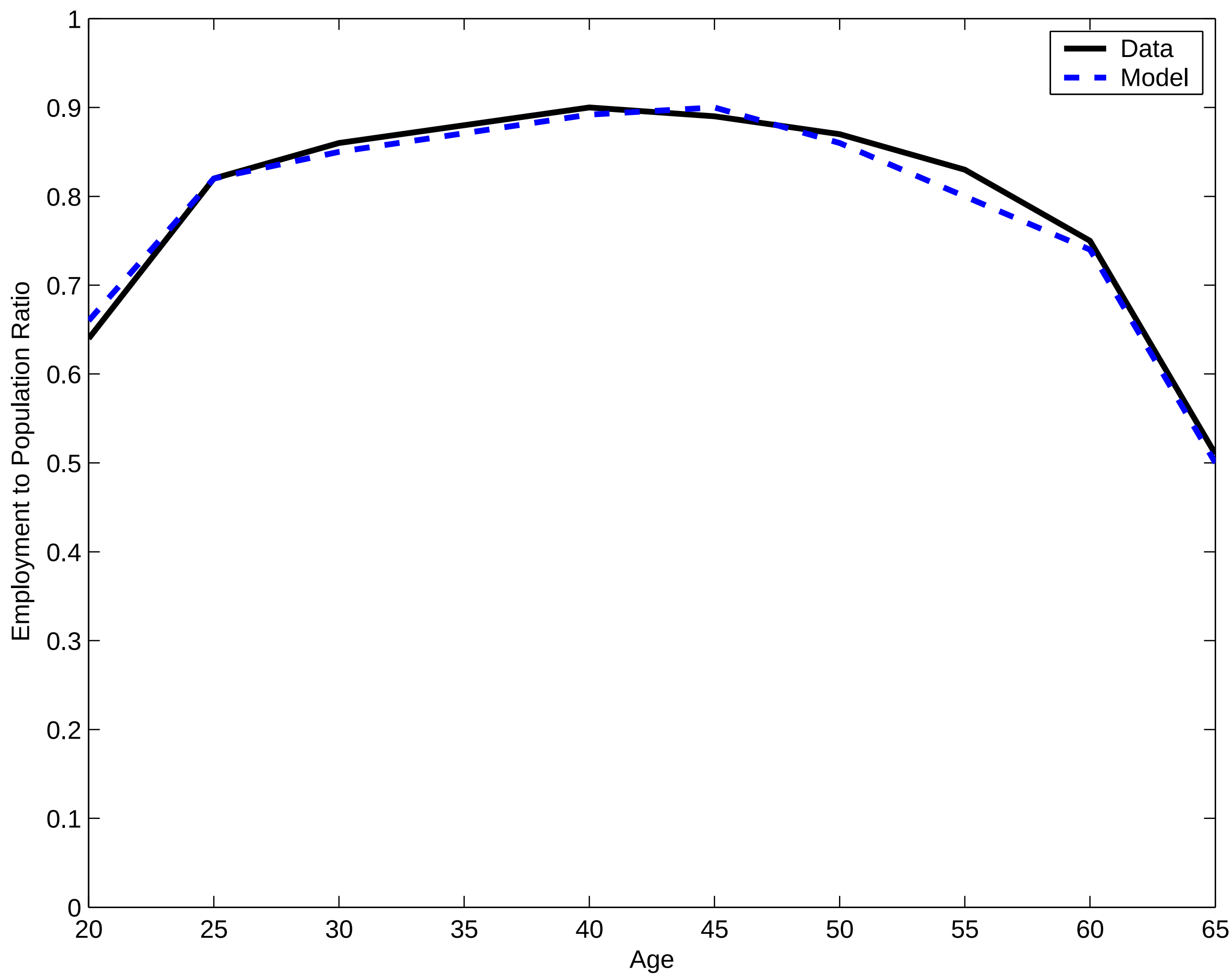


Figure 7: Age Profile of Wages - Males

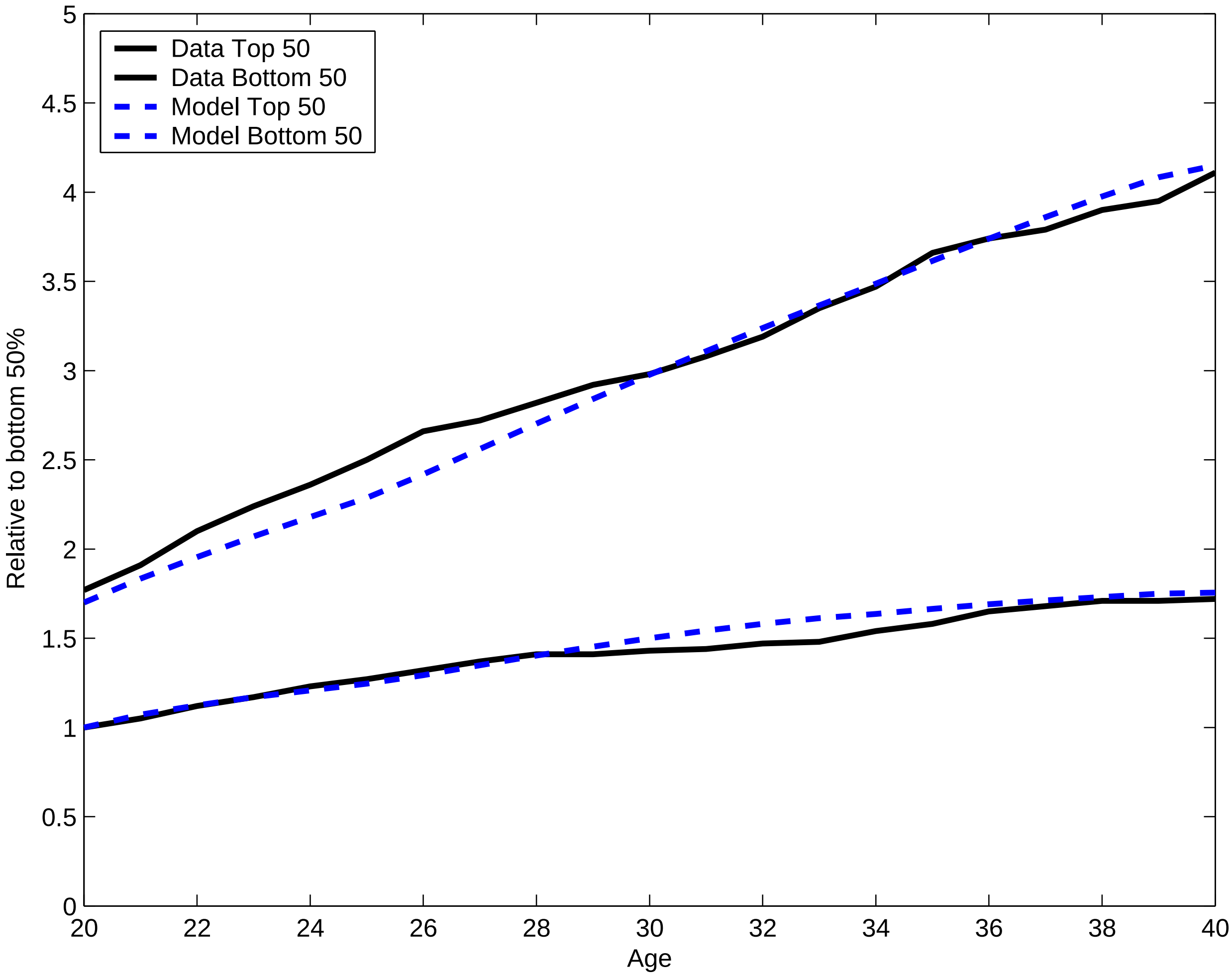


Figure 8: Experience Profile of Wages - Males

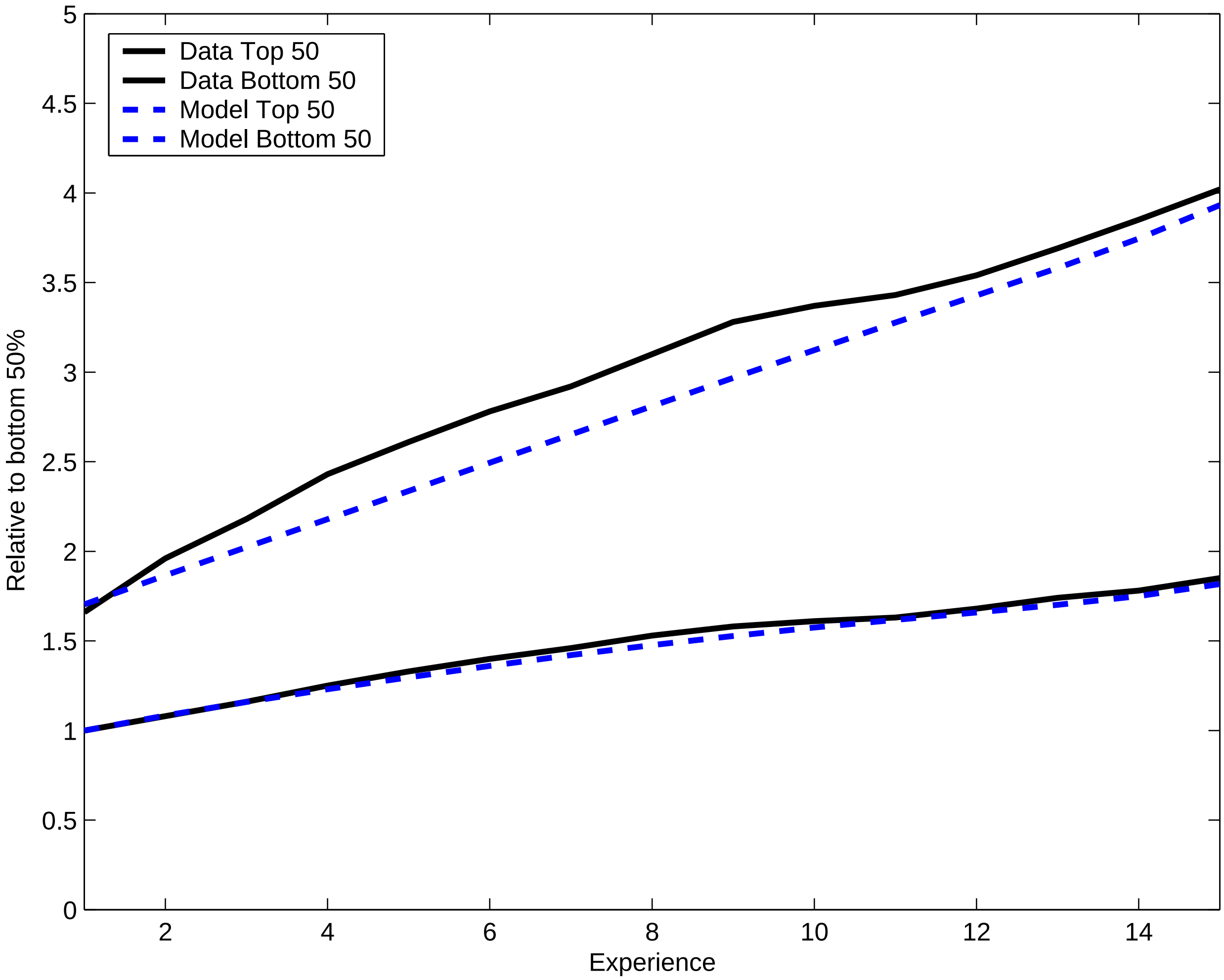
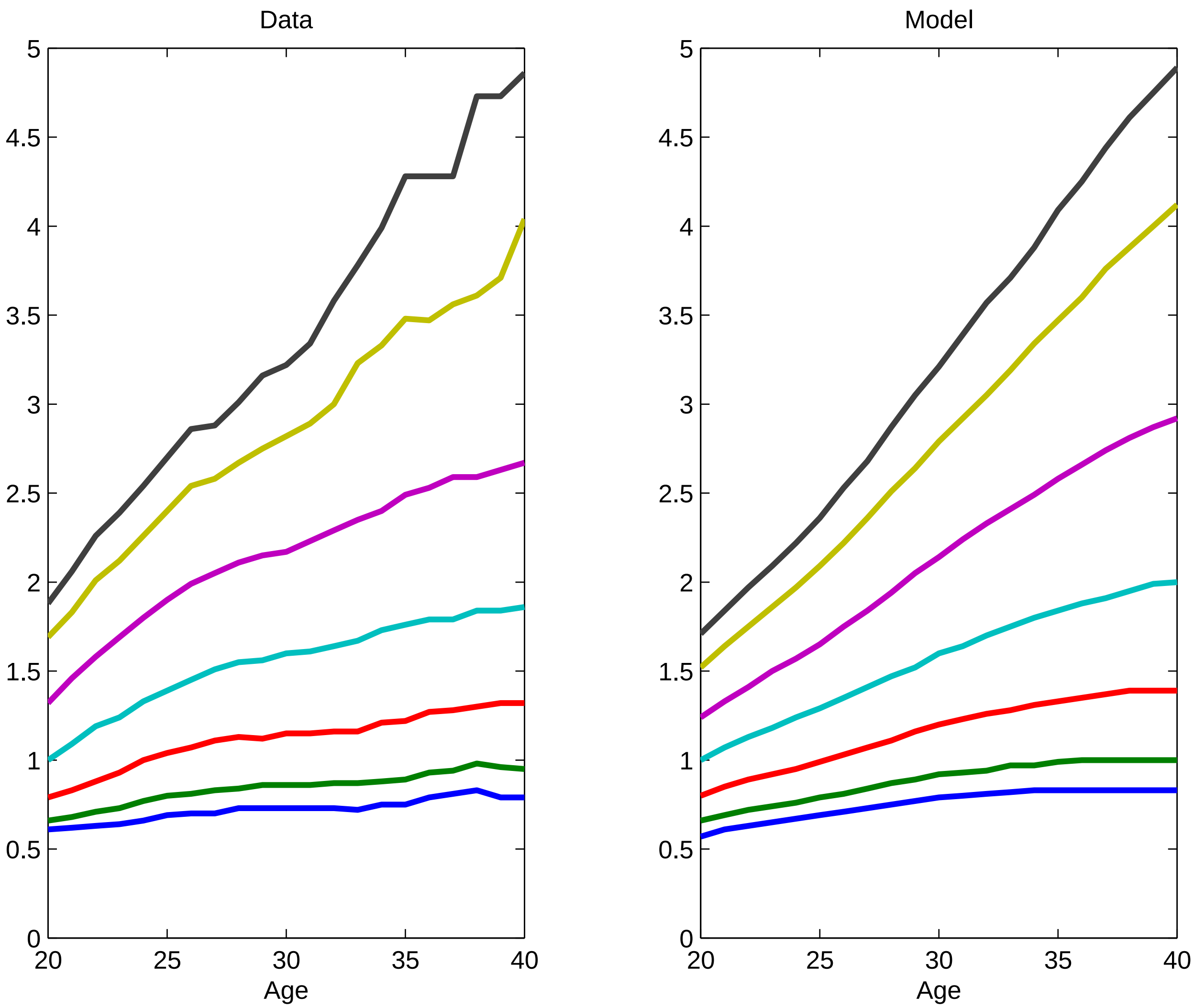
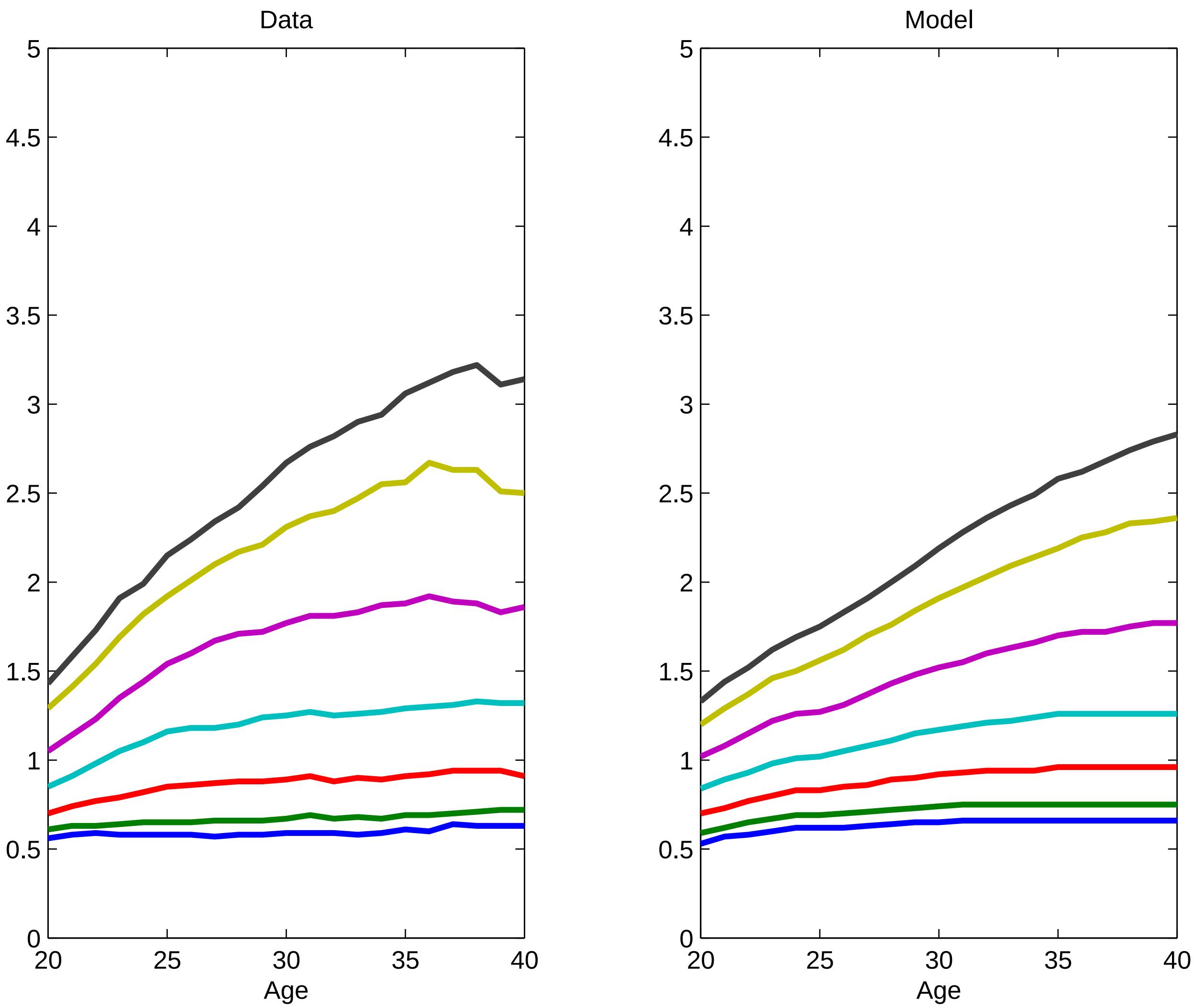


Figure 9: Age Profile of Wages - Males



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 10: 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.