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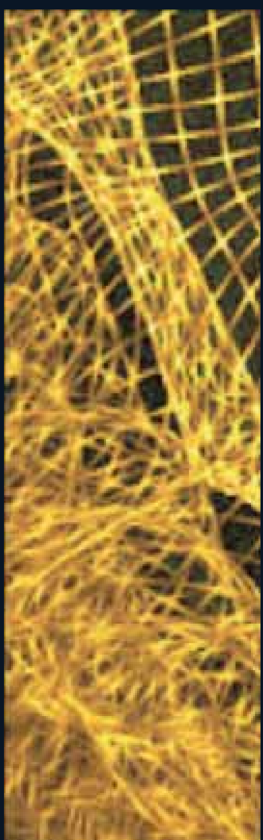

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A Quantitative Theory of the Gender Gap in Wages *

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Abstract

This paper measures how much of the gender wage gap over the life cycle is due to the fact that working hours are lower for women than for men. We build a quantitative theory of fertility, labor supply, and human capital accumulation decisions to measure gender differences in human capital investments over the life cycle. We assume that there are no gender differences in the human capital technology and calibrate this technology using wage-age profiles of men. The calibration of females assumes that children reduce the hours of work of mothers and that there is an exogenous gender gap in hours of work. We find that our theory accounts for all of the increase in the gender wage gap over the life cycle in the NLSY79 data. The impact of children on the labor supply of females accounts for 56% and 45% of the increase in the gender wage gap over the life cycle among non-college and college individuals. We also find that children play an important role in understanding the variation of the gender wage gap across recent cohorts of women and the slower wage growth faced by black women relative to non-black women in the U.S. economy.

JEL Classification: E24,J22,J24,J31. Keywords: Gender wage gap, employment, experience, fertility, human capital.

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1 Introduction

This paper measures how much of the gender wage gap over the life cycle is due to the fact that working hours are lower for women than for men. We build a quantitative theory of fertility, labor supply, and human capital accumulation decisions to measure gender differences in human capital investments over the life cycle. Clearly, any theory of gender differences needs to introduce some differences between males and females. While there are many ways one could introduce gender differences, our approach is to assume that the bearing and presence of children involve a forced reduction in hours of work that falls on females rather than on males and that there is an exogenous gender gap in hours of work.[1] We assume that there are no gender differences in the human capital technology and calibrate this technology using wage-age profiles of men. The model is calibrated to the fertility patterns and to the impact of children on career interruptions and labor supply of women in the data. The quantitative theory is then used to measure human capital accumulation of females during the life cycle.

Our investigation is motivated by some observations we document on NLSY79 data. We build detailed labor market histories of men and women and show that men work much more hours than women. Adding up weekly hours of work over the life cycle, we find that by age 40 the gender differences in cumulative hours of work are 45% among non-college individuals and 27% among college individuals. Gender differences in labor supply are accompained by substantial differences in wage growth over the life cycle. Over the first 20 years of labor market experience men's wages grow one percentage point higher per year than women's wages. We also document that children have an important role in generating gender differences in labor supply by comparing labor market histories of mothers and non-mothers.[2]

[1]Our decision-theoretic framework does not model the demand side of the labor market, which can also be a source of gender differences in wages. Albanesi and Olivetti (2005) show that, in the presence of private information on worker's labor market attachment, firms may use gender as a screening device and pay different wages to male and female workers.

[2]Because the negative association between children and female labor supply could be an artifact of selection, we provide evidence that -conditional on education- mothers are not self-selected from females with low labor market attachment. For details, see discussion of children and labor market outcomes in Section 2.

In our decision-theoretic framework individuals decide how much effort to exert in accumulating human capital on the job and whether to work or stay at home. Young females expect to work less than young males because females make fertility decisions which negatively affect their labor supply and because we assume an exogeneous gender gap in working hours. Gender differences in employment and working hours lead into gender differences in human capital investments, which translate into gender differences in returns to experience and a wage gap that increases with age. We find that the gender wage gap grows over the life cycle by 25 percentage points for non-college individuals and by 22 percentage points for college individuals. Altogether, the model accounts for all of the increase in the gender wage gap over the life cycle in the NLSY data for college individuals and slightly over predicts the increase in the gender wage gap for non-college individuals. We also find that the impact of children on the labor supply of females accounts for 56% of the increase in the gender gap in wages over the life-cycle of non-college females and for about 45% of the increase in the gender wage gap among college females, while the rest is due to exogenous gender differences in hours of work. 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 human capital accumulation on the job are high.

We evaluate the predictions of the theory for the gender wage gap across racial groups and across different cohorts of females. While in the U.S. black women tend to have more children than white women, the gender wage gap is lower among blacks than non-blacks. At first glance, this observation seems inconsistent with the predictions of our theory. Nonetheless, we use NLSY data on black non-college women and men to argue that the low gender wage gap among blacks is explained by the fact that black males work less and accumulate less human capital than the average male in the U.S. economy. Moreover, consistently with our theory, the data reveals that black non-college women work less hours and accumulate less human capital than the average non-college women. In a quantitative experiment, we show that racial differences in fertility behavior account for 44% of the difference in life cycle wage growth between black non-college women and the average non-college women in the NLSY data.

We also show that our theory is consistent with changes in the gender wage gap across cohorts. We use CPS data to document changes on fertility behavior and the gender wage gap for recent cohorts of American women. The evidence clearly indicates that the bulk of the decrease in the gender wage gap occurred for the cohorts of women born between 1941 to 1951 and that the timing of this decline coincided with the largest decrease in fertility across cohorts.[3] While the average number of children per women declined by 0.35 for college females and by 0.64 for non-college females across these cohorts, the life-cycle increase in the gender wage gap declined by 16 percentage points for college and by 27 percentage points for non-college individuals. Moreover, for college women the life cycle increase in the gender wage gap and the number of children remain roughly constant after the 1951 cohort. For non-college women, there was an important moderation in the decline of both the fertility rate and the gender wage gap after the 1951 cohort. We use our quantitative theory to evaluate how much changes in fertility behavior account for the variation in the gender wage gap between the cohorts born in 1941 and 1951. We change the baseline economy to mimic the main changes in fertility behavior observed when moving backwards from the 1951 to the 1941 cohorts. We find that changes in fertility behavior account for 37% and 44% of the change in the gender wage gap observed for non-college and college individuals between the 1941 and 1951 cohorts.

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).[4] These authors provide evidence that married women tend to interrupt their labor market attachment with periods of non-participation and, using

[3]We group cohorts in five year groups so that the 1941 and 1951 cohorts include women born in 1939-1943 and in 1949-1953.

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

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 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 uncertainty 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.

Our paper follows a recent tradition in quantitative theory on the economics of the family initiated by Aiyagari, Greenwood, and Guner (2000) and Regalia and Ríos-Rull (1998). 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 (2006) 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. 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. Our paper is related to a recent macroeconomic literature that studies female labor supply; Attanasio, Low, and Sánchez-Marcos (2004), Buttet and Schoonbroodt (2006), Cardia and Gomme (2009), Domeij and Klein (2010), Greenwood and Guner (2009), Greenwood, Seshardi, and Yorukoglu (2005), Jones, Manuelli, and McGrattan (2003), Knowles (2007, 2009), and Olivetti (2006). With the exception of Buttet and Schoonbroodt (2006) and Knowles (2009), these papers do not analyze the effects of changes in fertility behavior across cohorts.[5] Our paper contributes to this literature by showing that a decrease in fertility can lead to both an increase in the labor force participation of women and to an increase in the return to experience faced by women.[6]

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 (2002, 2010) 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 when substantial investment in human capital occurs.

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

2 Data

We use a panel data from the National Longitudinal Survey of Youth (NLSY79) to document observations characterizing the behavior of a recent cohort of young men and women in the

[5]Da Rocha and Fuster (2006) use their quantitative theory to investigate recent cross-country observations on fertility and female labor market participation rates.

[6]Guner, Kaygusuz, and Ventura (2010) analyze how taxation affects labor force participation of women and the returns to experience faced by females.

labor market. We emphasize three observations from these data. First, gender differences in wages grow substantially over the life cycle. Second, on average men work much more over the early part of the life cycle than women. Third, the origin of the gender differences in labor supply can be traced to the impact of children in labor market decisions of women. In what follows we document these observations in detail.

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

Gender Differences in Wages A salient feature of the labor market is that the average hourly wage of women is substantially lower than the average wage of men. In our sample of the NLSY79, the average wage ratio between women and men is 0.78. Although wages grow substantially over the life cycle for both men and women, the gender wage ratio decreases over the life cycle −the gender gap in wages increases with age (see Figures 1 and 2). The increase in the average wage over the life cycle for men and women for both educational types is shown in Figure 1. Whereas the average wage of non-college individuals increases between age 17 to age 40 by a factor of 2.45 for men, it increases by a factor of 1.95 for women. The gender difference in wage growth for non-college individuals is on average about 1 percentage point per year and accounts for an increase in the gender wage gap between ages 17 to 40 of about 20 percentage points. For people with college education, the average wage between age 23 to age 40 increases by a factor of 2.28 and 1.77 for men and women, respectively. These observations imply a gender difference in wage growth of 1.3 percentage points per year and an increase in the gender gap between ages 23 to 40 of 20 percentage points. Altogether, the fact that men more than double their wages in a 20 year period suggests that there are important human capital investments over the life-cycle. Human capital theory suggests that the returns to human capital investments depend on how much hours people expect to work in the future. If men and women differ with respect to their actual or expected attachment to the labor market, their incentives to invest in human capital would differ as well. Hence, human capital theory suggests that it is important to evaluate the extent of gender differences in labor supply in the data.

Employment and Hours On average non-college men work 46% more hours than non-college women (36.2 vs. 24.7 hours per person per week, 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).[7] We also find substantial gender differences in labor supply among college individuals. College men work 33% more hours than college women, with gender difference in hours per worker accounting for 60% of the total difference in hours of work.

Figures 3 and 4 document the life-cycle path of average hours per-worker and the employment to population ratio for men and women for both educational types. Among non-college, hours per worker and the employment to population ratio increase with age for both men and women, but employment is more prevalent for men than for women at every age group. While the employment to population ratio is about 7 percentage points higher for men than for women at age 17, by age 40 this difference is 13 percentage points. There is also a substantial gap in hours of work among people working: At age 17, employed men spend 4 hours more working per week than women. At age 40 the difference in hours of work is 9 hours per

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

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

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

Table 1: Average Hours and Employment

	Non-College*			College**		
	Men	Women		Men	Women	
		All	No Child†		All	No Child
Hours per person (week)	36.2	24.7	32.8	41.6	31.2	36.7
Hours per worker (week)	44.2	36.9	40.5	46.2	39.0	42.7
Employment to population ratio	0.82	0.67	0.81	0.82	0.67	0.81

*People 20 to 43 years of age. **People 23 to 43 years of age. †No Child refers to women with no children (until the last observation in our sample, when women are 37 to 44 years old).

week. Similarly, we find that the gender differences in hours worked and employment rate expand over the life-cycle for college educated individuals. Interestingly, we find that the employment rate and hours per worker of college educated women decrease with age during the child-rearing period.

Children and Labor Market Outcomes Labor supply differences across gender are substantial. What is striking in comparing labor market outcomes of men and women is the role that children play in labor supply decisions of women. We compare statistics for the average of all women and for the average of women who never had children.[8] For the non-college type, the employment to population ratio of women with no children is almost identical to that of men during the life cycle as documented in Figure 3. The pattern of average hours per worker is also similar between non-college men and women with no children except for a constant gap (roughly 5 hours per worker per week or about 10% of the hours per worker of males) (see Figure 4). Among the college educated, we also observe that women with no children work more often and more hours than the average women.[9]

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

[9]Interestingly, while non-college women with no children work as often as men, the employment rate of college women with no children is lower than the one of men (see Figure 3). A possible explanation for the

The fact that there is a negative association between children and female labor supply in the data, does not necessarily imply that children have a negative effect on female labor supply as this empirical relationship could well be due to selection: Women can be heterogeneous in their labor market attachment and mothers could be drawn from workers with low preferences for work. To address this concern, we discuss data suggesting that children have a negative impact on female labor supply. A first clue of the role of children is in Figure 3: Gender differences in labor supply grow substantially at the ages when women start bearing children. While for non-college individuals the gender differences in employment rates grow substantially after age 23 and start diminishing rapidly before age 30, for college individuals the employment rate only differs across genders after age 26 and these differences are still substantial by age 40. These patterns are consistent with the fact that college educated women tend to give birth at older ages than less educated females and with the view that children -of young age- negatively affect the labor supply of mothers. Table 2 documents that the employment rates between mothers and non-mothers differ substantially, particularly when children are young. While women with no children have an average employment to population ratio similar to the average of men (81% vs. 82% for non-college and 86% vs. 90% for college), women with at least one child under 6 years of age have employment to population ratios below 60% in the case of non-college women and below 73% in the case of college women. The employment ratio of women with young children (less than a year old) is lower than 45% in the case of non-college and 62% in the case of college. The fact that the employment rate of mothers grow substantially with the age of their youngest child, suggests that the low employment rate of mothers is not due to permanent differences in the labor market attachment between mothers and non-mothers.

More direct evidence on the importance of children in generating gender differences in labor supply can be obtained by exploiting the panel dimension of our NLSY data. We do this in three ways. First, we show that the duration of non-employment spells differs substantially across genders and that children play a crucial role in accounting for these observations. We divide all non-employment spells of women between spells that involve

different behavior of women with no children across educational types is that college women marry wealthier men than non-college women.

Table 2: Average Hours and Employment

	Non-College			College		
	H./P.	H./W.	Emp.	H./P.	H./W.	Emp.
Men	36.2	44.2	82.0	41.6	46.2	90.0
Women	24.7	36.9	67.0	31.2	39.0	80.0
Women without Children	32.8	40.5	81.0	36.7	42.7	86.0
Women by Number of Children under 6:						
1	20.7	36.6	56.7	25.8	35.7	72.4
2	14.9	34.8	42.9	19.8	33.0	60.0
3 or more	10.6	34.1	31.0	14.7	32.2	45.8
Women by Age of Youngest Child:						
Less than 3 months	10.2	35.5	28.7	16.7	34.8	48.2
3 to 6 months	14.0	34.8	40.0	19.7	34.2	57.8
6 to 9 months	15.1	34.6	43.8	20.7	33.9	61.1
9 to 12 months	15.7	34.8	45.2	21.1	33.9	62.4
1 to 5 years	19.4	36.1	53.8	24.0	34.8	69.0
5 to 6 years	23.7	37.4	63.5	27.7	36.1	75.7

the birth of one child at the time or during the job separation (we call these spells "birth") and spells that do not involve the birth of a child ("No birth").[10] An important fraction of all non-employment spells do not involve the birth of a child (almost 82%) and the average duration of these spells is similar to that of men (46 weeks for men vs. 50 weeks for women

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

in the case of non-college and 42 weeks for men vs. 38 weeks for women in the case of college). Table 3 documents that 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 (46 weeks for men vs. 113 weeks for women in the case of non-college group and 42 weeks for men vs. 102 weeks for women in the case of the college category). As documented below, the gender differences in the duration of non-employment spells translate into important differences in accumulated labor market experience.

Table 3: Duration of Non-Employment Spells

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

Second, to document that children have a direct causal effect on female labor supply, we examine labor market decisions of mothers before and after childbirth for all birth episodes in the NLSY. Figure 5 shows that the employment rate decreases during pregnancy and that it slowly recovers after childbirth. For both education groups, the employment rate one year after birth is still more than 10 percentage points below its level prior to pregnancy. Third, we provide evidence that -conditional on education- mothers do not differ from non-mothers in terms of their attachment to the labor market. This is important for the following reason: While our quantitative theory allows for differences in fertility and human capital accumulation across women of different education groups, our findings may exaggerate the role of children if, after controlling for education, there are important differences in labor market attachment across mother and non-mothers in the NLSY data.[11] To evaluate this possibility, we partition the population of women in the NLSY in two groups: The first group is comprised by the women who have not become mothers by the last NLSY interview. We refer to this group as women with no kids ever (women NKE). The second group includes women who have become mothers at some point. Figure 6 compares the employment rate of women with no kids ever with the employment rate of mothers one year before they had their first child. The figure reveals that mothers, prior to giving birth to the first child, do not appear to have lower employment rates than women with no kids ever. Figure 7 shows that average working hours, conditional on employment, are quite similar for women with no kids ever and for mothers one year giving birth to their first child. Altogether, the evidence in Figures 6 and 7 suggest that there are no differences in labor market attachment between mothers, prior to giving birth to their first child, and women with no kids ever. We interpret this evidence as suggesting that mothers are not self-selected from a group of women with low labor market attachment. This interpretation is consistent with the findings of Light and Ureta (1995). These authors use NLS data to estimate proportional hazard models of career interruptions that allow for the presence of unobserved heterogeneity. While their estimates imply considerable unobserved heterogeneity among women for early cohorts in their study, they conclude that for women born after 1950 unobserved heterogeneity becomes an insignificant factor and that the only important determinant of women's turnover is the presence of young children (see Light and Ureta (1995), page 179).

The Accumulation of Experience Women are characterized by lower employment, fewer hours of work, and longer duration of non-employment spells than men. These gender differences in labor supply imply that on average, women accumulate less experience in the labor market than men. Table 4 documents the average accumulated experience for men and women at age 40 in our panel data, for two measures of experience: Accumulated weeks

[11]While individuals might also differ in terms of cognitive ability, Cawley, Heckman , and Vytlacil (2001) argue that measures of cognitive ability and schooling are so strongly correlated that one cannot separate their effects on labor market outcomes without imposing arbitrary parametric structures in estimation which, when tested, are rejected by the data.

of work and accumulated weekly hours of work.[12] Table 4 indicates that by age 40, non-college men have accumulated 22% more weeks of experience than non-college women, and 45% more hours of work than non-college women. The gender differences in labor market experience are lower but still substantial for the college type. (see Table 4). Women with children accumulate much less experience (measured in hours) than men, 53% less in the case of non-college women and 33% less in the case of college women. We emphasize that the gender differences in experience that we obtain by adding up hours of work over the life-cycle in Table 4 are much larger than the ones implied by commonly used measures of experience such as potential experience (age-years of schooling-6) or actual experience (accumulated years of employment). We conclude that the large gender differences in cumulative hours of work, suggest that women face much lower incentives to accumulate human capital than men.

Table 4: Accumulated Experience at Age 40 (years)

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

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

[12] 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.

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. We assume that the population is divided in two (exogenous) education groups representing college and non-college individuals. While preferences, human capital accumulation technology, and shocks are assumed to vary across education types, we do not index parameters and variables with an education index to keep the notation as simple as possible. To keep our analysis simple, we abstract from marriage, inter-temporal consumption smoothing, and general equilibrium interactions.[13] Below we present the key ingredients of our framework.

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

Labor Decision 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, education, 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.

[13] Our theory can accommodate by assuming that matching is independent of fertility, labor market, and human capital decisions. Extending the theory to model a non-trivial joint decisions by husband and wifes is a daunting task since we would need to model three endogenous state variables (asset accumulation and human capital of husbands and wives) together with discrete (non-convex) labor-participation and fertility decisions.

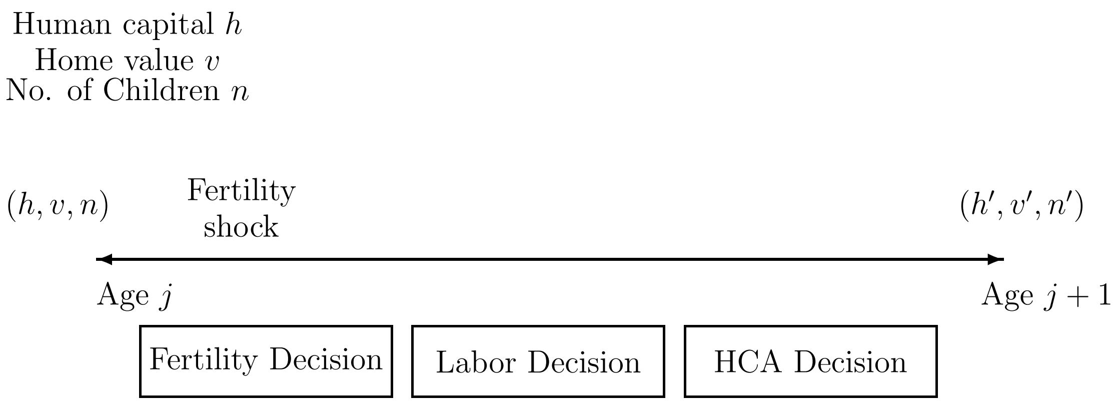
Human Capital Accumulation Decision We model human capital accumulation while working. The technology to accumulate human capital varies across education groups. We assume that workers who exert effort e increase their human capital by a proportion $\triangle$ with probability e. The utility cost of 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 for each education type. 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.[14] 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. Moreover, this assumption allows our model to generate a reasonable age-profile of fertility for each education group.

Timing of Decisions Below, we draw a time line representing the timing of decisions within a period in our model for an individual in an exogenously given education group. 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

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

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,

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

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

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 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 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. For each educational type, 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 for each education group. We model the decisions of non-college individuals since age 17 since women between age 17 to age 19 account for 20% of all the births among women in this education group. College individuals are modeled since age 20. The mapping between parameter values and targets in the data is multidimensional and we thus solve for parameter values jointly. For expositional reasons, we next describe the role of each parameter on a specific target as if the parameter has a first-order impact in the target. In the appendix, we report the calibrated parameter values for non-college and college individuals (see Table 20).

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, $l(j)$, younger than 41 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 5.

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 which is independent across individuals. 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 (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 when individuals enter the labor market, they make a draw of their initial human capital from a log-normal distribution. We first discuss the calibration of the human capital technology for the non-college group. The mean of log human capital is normalized to 2 (the lowest log human capital is normalized to 0) and the standard deviation, σ_{h_0}, is chosen so that the coefficient of variation of wages for male workers of age 17 matches the 0.36 value in the NLSY79 data for non-college individuals. 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 the age profile of wages for two groups of non-college workers in the data. In particular, we focus on the average wage for people at the bottom and top 50% of the distribution of wages at each age. The calibration for college individuals is done similarly but targeting data on wages after age 23.[15]

Table 5: Calibration for Males

Parameter	Target
v_j	Employment by age
ρ	Duration of non-employment spells
σ_{ϵ_s}	Average experience at age 40
σ_{h_0}	C.V. wage at age 17 for non-college and age 23 for college
$(\alpha_1, \alpha_2, \Delta, \gamma_h)$	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

[15] In this way we achieve a compromise between targeting wage growth over a long period of time and ensuring that the wage data comes from individuals that have completed schooling or are close to finish their college education

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 σ_{h_0}. 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 an appendix in Table 20.

4.2 Calibration for Females

Preference for Children and Fertility Opportunities For each educational type, we select the preference parameter for the number of children γ_n to match the total fertility rate in the NLSY79 data. We assume that fertility opportunities are constant within four age groups but differ by number of children (0, 1, 2, and 3 or more).[16] 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 7. The parameter values obtained in the calibration are reported in the appendix.

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 μ_{v_c}. For each educational type, the parameter μ_{v_c} is selected to match the employment ratio of women

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

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). In addition, we assume that children reduce the hours worked until their mother becomes 40 years old and that such cost depends on the age of the female.[17] In order to parametrize the time cost of children, we estimate a fixed effects regression model using our NLSY79 sample. The dependent variable is weekly hours worked (conditional on being employed) and the explanatory variables are linear, quadratic and cubic terms on age, the number of children under 18 of age, and an interaction term on the age of the mother and the number of children younger than 18. The estimated coefficients for both college and non-college types are shown in Table 6. Based on this regression model, we assume that the time cost per child is a function $\tau + j * \tau_1$ where j denotes the age of a mother and that the parameter $\tau = 6.81$ and $\tau_1 = -0.133$ for the case of non-college and $\tau = 12.56$ and $\tau_1 = -0.239$ for the case of college. Given that on average a non-college female has her first child at the age of 22.5 and the second child at the age of 26, the assumptions on the time cost of children imply that a mother's working time is reduced by 3.9 hours by the first birth and by 3.3 hours by the second birth.[18]

Summarizing We select the values of 9 parameters for each educational type: 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 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

[17] Table 2 shows that the hours worked by mothers increase with the age of children. We approximate this relation by assuming that the time cost of children is a decreasing function of the age of the mother. In this way, we reduce the dimensionality of the problem as we do not need to carry as state variable the age of each child, which computationally could be quite costly with a quarterly model period.

[18] Given that in the baseline economy college females have, on average, the first and second child at ages 27.8 and 30.6, the parameterization above implies an average time cost of first and second births of 5.9 hours and 5.2 hours for college females.

Table 6: Fixed Effects Panel Regression: Hours Worked by Women

Regressor	Non-College	College
Age	3.32	16.09
	(.476)	(.78)
Age^2	-.086	-.44
	(.015)	(.025)
Age^3	.0007	.0039
	(.0001)	(.0002)
$Children$	-6.81	-12.56
	(.33)	(.757)
$Age * Children$	.133	.239
	(.009)	(.020)
$Intercept$	.196	-147.8
	(4.82)	(8.01)

data.

4.3 Calibration Results

We now discuss how the model matches the calibration targets. Figure 8 reports the employment ratio by age of males for the model and the data. For both educational types, 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 18.6 years for non-college and 17.8 years for college of accumulated experience while the same statistic in the data is 17.9 and 17.2 years respectively. This average experience is generated from a reasonable distribution of years of experience in the model relative to the data (see Table 8).

The model matches quite closely the life-cycle wage growth for the average male in the

Table 7: 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

Table 8: Distribution of Accumulated Experience (weeks) - Males

	Non-College*		College**	
	Data	Model	Data	Model
Average (years)	17.9	18.6	17.2	17.8
Distribution (%):				
< 17 years	29.6	21.3	31.6	26.2
$[17, 19)$ years	18	30.2	41.1	48.2
$[19, 23)$ years	51.4	48.5	27.3†	25.6†

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

†Between 19 and 21 years of experience.

bottom 50% and in the top 50% of the wage distribution for each educational type (see Table 15). Moreover, the model also captures reasonably well the heterogeneity in wage growth by age at different points of the wage distribution for males of each educational type (see Figures 9 and 10). The calibration targeted the duration distribution of non-employment spells, which the model matches well (see Table 9).

Regarding the calibration targets for women with children, Table 10 reports the total fertility rate, birth rates by age, and the distribution of number of children for females at age 40. For both education groups, the model matches the average fertility rate and the birth rates by age. The model is also consistent with the distribution of women at age 40 by number of children in the data: About 14% of non-college females do not have children, 54%

Table 9: Duration Distribution of Non-employment Spells - Duration weeks (%)

	Non-College		College	
	Data	Model	Data	Model
1 quarter (7-19)	46	43.6	44	47.3
2 quarters (20-32)	20	20	18	20.7
3 quarters (33-45)	11	12	18	11.4
4 quarters (46-58)	6	7.6	7	10
More than a year (> 58)	17	16.8	13	13.6

have one or two children, and 32% have 3 or more children. In the case of college women the distribution is as follows: 27% do not have children, 52% have one or two children, and 21% have 3 or more children.

Table 11 reports the employment to population ratio of females by age of the youngest child in the model compared with the data. For both education groups, the model matches well the pattern of low employment for females with young children.

Table 12 documents the duration distribution of child related non-employment spells in the model and in the data. The model does a pretty good job in matching the data along this dimension.

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 two 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. Second, females work 10% less hours than males when employed (exogenous hour gap), regardless of whether they have children or not. 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

Table 10: Fertility Rate, Birth Rates by Age, and Distribution of Females at Age 40 by Number of Children

	Non-College		College	
	Data	Model	Data	Model
Average Fertility	1.95	1.95	1.54	1.55
Birth Rates: (%)				
17-19	17.5	17.4	2.1	0
20-24	32.5	29.8	11.0	11.5
25-29	28.4	27.9	31.7	32.8
30-34	15.1	15.3	37.3	39.8
35-40	6.5	9.6	17.9	15.9
Female Distribution by Number of Children: (%)				
0	14.0	14.1	27.3	26.5
1	18.6	18.9	14.4	16.4
2	35.2	35.8	37.7	38.4
3	20.5	20.2	13.8	12.2
≥4	11.7	11	6.8	6.5

the 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. The model implies a slightly shorter duration of the non-employment spells of non-college females relative to the data (see Table 13). Overall, the model generates large gender differences in labor supply, albeit smaller than in the data for non-college. In effect, by age 40, among

Table 11: Employment Ratio of Mothers by Age of Youngest Child

	Non-College		College	
	Data	Model	Data	Model
Age of Child:				
1 quarter	27	30	48.3	45.8
2 quarter	38	38.5	57.8	54.5
3 quarter	42	43	61.6	58.3
4 quarter	44	46	62.4	61
$[1, 5)$ years	53	60.5	69.0	74.4
$[5, 6)$ years	63	73.7	75.7	86.6

non-college individuals the gender difference in total hours of work in our model is about 34%, while this statistic is 46% in the data. In the case of college individuals, the model reproduces the observed gender difference in labor supply: Between ages 20 to 40 college men accumulate 30% more hours of experience than college women (see Table 14).

Wages of Females in the Life Cycle We now present the main finding of the paper: Our quantitative theory of human capital investments accounts 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 between age 17 to age 40 the wages of non-college females grow by a factor of 1.95 in the data, they grow by a factor of 1.83 in the model. Moreover, the model matches the fact that wages of college women grow by a factor of 1.77 between ages 23 and 40.

Our theory also has implications for the cross-sectional distribution of wages along the life-cycle (see Table 15). While the wage growth of males was a target of our calibration strategy, wage growth for females is the result of their investments in human capital which are affected by their lower labor supply relative to males. The fact that females have children and that children reduce their labor supply will have consequences for wage growth which are not calibrated. Table 15 reports the wage growth at the bottom 50% and at the top

Table 12: Duration Distribution of Non-employment Spells of Mothers (%)

	Non-College†		College*	
	Data	Model	Data	Model
1 quarter (7-19 weeks)	16	13	21	19.5
2 quarters (20-32)	8	8	9	10
3 quarters (33-45)	8	6	7	7
4 quarters (46-58)	6	6	5	5.5
More than a year (> 58)	62	67	58	58

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

50% of the wage distribution in the model and in the data. Overall, the table shows that our theory can account well for the slow life cycle wage growth of females across the wage distribution although the matching of the data is not perfect. In the case of non-college, the model understates the life cycle wage growth of the two groups of females (at the top and at the bottom 50% of the distribution of wages). In the case of college, the model matches the life cycle wage growth of females at the top 50% while it overstates the wage growth of females at the bottom 50% of the wage distribution.

The Gender Gap in Wages In the model economy, the gender differences in wage growth imply an increase in the gender wage gap of 25 percentage points for non-college women (between age 17 to age 40) and of 22 percentage points for college women (between age 23 to age 40). These statistics are 21 and 22 percentage points in the NLSY data. Hence, the model accounts well for the increase in the gender wage gap. Our finding is consistent with that of Bertrand et al. (2009) who find that the large growth in the gender gap for MBAs during their first 15 years out is mainly a consequence of gender differences in career interruptions and weekly hours worked.

Recall that in our model there are two channels generating gender differences in labor supply and, hence, in the returns to human capital investments: children and the exogenous differences in hours of work. In order to evaluate the quantitative importance of each of these

Table 13: Duration Distribution of Non-employment Spells (%)

	Non-College†		College*	
Duration (weeks):	Data	Model	Data	Model
1 quarter (7-19)	37.4	40.8	49	44.6
2 quarters (20-32)	16.0	18.6	15	19.6
3 quarters (33-45)	10.3	11.1	12	10.6
4 quarters (46-58)	6.7	7.1	6	6.6
More than a year (>58)	29.6	22.4	18	18.6

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

Table 14: Average Accumulated Hours of Experience (in years)

	Non-College†		College*	
	Data	Model	Data	Model
Males	20.3	20.8	19.6	19.9
Females	13.9	15.5	15.2	15.3
Males/Females	1.46	1.34	1.29	1.30

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

channels, we consider two experiments. In a first experiment, we shut down the exogenous gender differences in hours of work and assume that the only source of gender differences in labor supply are due to children. As in the baseline economy, we assume that women who give birth draw an stochastic value of staying at home with their children so that they may go through a non-employment spell. Moreover, we assume that children reduce working hours of employed mothers as in the baseline economy. We refer to this experiment as the "only children" economy. In a second experiment, we assume that there is an exogenous gender-hour gap of 10 percent, just as in our benchmark economy. To isolate the role of this channel, we assume that women do not have children. This experiment gives the "only hours" economy. The results from these experiments are summarized on Table 16.

Table 15: Wage Growth

	Non-College†				College*			
	Males		Females		Males		Females	
	Data	Model	Data	Model	Data	Model	Data	Model
Average	2.44	2.44	1.95	1.83	2.28	2.28	1.77	1.77
Top 50%	2.85	2.85	2.26	2.15	2.37	2.36	1.88	1.86
Bottom 50%	1.84	1.83	1.48	1.38	2.15	2.15	1.56	1.64

† Ratio Age 40/age 17. * Ratio age 40/age 23.

We find that in the "only children" economy the gender wage gap increases over the life-cycle by 14 percentage points for non-college females and by 11 percentage points for college females. Comparing with the findings in the baseline economy, we conclude that the contribution of children to the increase in the gender wage gap over the life-cycle is 56% for the non-college type (14 percentage points out of an increase of 25 percentage points in the baseline economy) and 45% for the college type (10 percentage points out of an increase of 22 percentage points in the baseline economy). In the "only hours" economy, we find that the gender wage gap increases over the life cycle by 11 percentage points for non-college and by 9 percentage points for college females. Comparing with the findings in the baseline economy, the results from the second experiment implies that the contribution of children to the gender wage gap is 56% for the non-college type and 50% for the college type. Altogether, the impact of children on the labor supply of mothers contributes for at least 45% of the increase in the gender gap in wages over the life-cycle. This effect is larger for non-college than for college educated females for two reasons: First, non-college females have more children and they have children earlier in the life cycle at a time when the return to human capital investments is higher. Second, the non-employment spells related to birth are longer for non-college females than for college females.

Discussion Our theory abstracts from time trends in prices that could have favored relatively more women than men. Bacolod and Blum (2010) present evidence that in the U.S.

Table 16: Contribution of Children to the Increase in the Gender Wage Gap

	Non-College[†]		College[*]	
	△ Wage Gap	Contribution	△ Wage Gap	Contribution
Benchmark	0.25	of Children	0.22	of Children
Only Children	0.14	56%	0.10	45%
Only Hours	0.11	56%	0.11	50%

[†]Between ages 17 to 40. [*]Between ages 23 to 40.

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. Had we modeled changes in prices that favor females relative to males, our theory would have predicted a higher life cycle wage growth of females and a lower gender wage gap. The effects of children on human capital accumulation would have not diminished as long as the calibration would have kept constant the targets for fertility and the impact of children on labor supply. Hence, the contribution of children to the overall gender wage gap would have been larger.

Our results do not rule out the possibility of labor market discrimination. In fact, the exogenous gender differences in labor supply that we assumed could (partly) be due to labor market discrimination. While our theory focuses on the role of children as an "impulse" and on the interaction of labor supply and human capital over the life-cycle as a propagation mechanism, labor market discrimination can be thought of as alternative (or complementary) impulse. We focus on the impact of children for labor supply and wages because children are measurable and have a first order impact on the labor supply of women. Moreover, by focusing on children as an impulse, we can use the variation in number of children across racial groups and across recent cohorts of U.S. women to test the predictions of the theory. Adding labor market discrimination to our model would not reduce the quantitative importance of children in our theory. Obviously, discrimination alone could not account for the facts on the gender wage gap since discrimination would need to be coupled with our human-capital mechanism for the theory to be capable of generating the increase in the gender wage gap over the life cycle. Whether discrimination plays an important role in generating gender differences in labor supply or not, a key message of our paper is that human capital and labor supply factors can account for the overall increase of the gender wage gap in the life-cycle.

6 Other implications of the theory for gender differences in wage growth.

Our findings point that children have a large negative effect on the rate of growth of female wages over the life-cycle. Since fertility varies substantially across racial groups and across different cohorts of females, it is interesting to evaluate the predictions of the theory along these dimensions.

6.1 Race and the Gender Wage Gap

While in the U.S. black women tend to have more children than white women, the gender wage gap is lower among blacks than among non-blacks. At first glance, this observation seems inconsistent with the predictions of our theory. Nonetheless, we now show that the theory is consistent with data on gender differences in wage growth across races. We use NLSY data (with the oversample of blacks) to document some facts on gender differences in labor supply and wages among black individuals. Due to small sample sizes, the analysis is restricted to individuals with non-college education.[19] The main findings are:

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

[19] We compute all the statistics documented in Section 2 only for non-college black men and women since we have few observations for college educated black individuals.

30% of births occur before age 20 for black non-college women while such percentage is 18% for all non-college women.

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

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

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

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

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

Fact 5 shows that black non-college women face lower wage growth than the average non-college woman. Despite the low wage growth of black non-college women, by age 40 the gender wage gap among black non-college individuals is smaller than that of the overall non-college population (Fact 3). The low gender wage gap for blacks is explained by the fact that black males work very little and accumulate little human capital relative to other males in the U.S. economy (Fact 4).[20] Thus, the low gender wage gap among black non-college individuals does not contradict our view that children have a negative impact on female wage growth. In fact, consistently with our theory, the data reveals that black women work less (Fact 2) and accumulate less human capital (Fact 5) than the average non-college woman in the economy. Our theory points that black females face low returns to human capital accumulation because they expect to have more children and, hence, to work less than other non-college females in the economy.

We now evaluate the quantitative predictions of the theory. We ask: Can racial differences in fertility behavior account for the low wage growth faced by black non-college women relative to the average non-college woman in the U.S. economy? To answer this question, we use our model to perform a counter factual experiment. This experiment consists in changing the fertility behavior of non-college women in the baseline model in order to match the fertility rates by age of black non-college women in the U.S. data. This is done by recalibrating the parameters determining fertility opportunities. We also recalibrate the parameter determining the mean of the distribution of the value of staying at home with children in order to match the employment rate of black mothers by the age of the youngest child.[21] All the other parameters of the baseline economy are kept constant. As shown in the Appendix, the re-calibrated model fits well the targeted employment rate of mothers and the fertility statistics of black non-college women (see Tables 22 and 23).

The main finding of this experiment is that the average wage growth from age 17 to age 40 decreases from a factor of 1.83 to a factor of 1.75 when non-college women exhibit the fertility behavior of black non-college women (see Table 17). This reduction accounts for 44% of the difference in life-cycle wage growth between black non-college women and the average non-college women in the NLSY data. We conclude that fertility decisions play an

[20]The question of why black males work few hours in the labor market is important but out of the scope of the current paper.

[21]The values of the recalibrated parameters are reported in Table 21 in the Appendix.

important role in understanding the low wage growth faced by black non-college women in the U.S. economy.

Table 17: Race Experiment: Wage Growth of Females†

	Data	Model
Black Non-College	1.77	1.75
All Non-College	1.95	1.83
Ratio	0.91	0.94

†Between ages 17 to 40.

6.2 The Gender Wage Gap across Cohorts

It is well known that there have been important changes in fertility decisions and in the gender wage gap across recent cohorts of American women. Since our theory implies that fertility decisions have important consequences on female human capital accumulation and, hence, on the evolution of the gender wage gap over the life-cycle we ask: Can changes in fertility behavior across recent cohorts of women account for the evolution of the gender wage gap over time -both the decline and the timing of the decline?

To answer the above question, we use CPS data to document changes on fertility behavior and the gender wage gap for recent cohorts of American women.[22] Figure 11 documents that fertility declined substantially between the cohorts of women born in the 1940s and 1950s for both college and non-college educated women, and that the decrease in fertility has been more pronounced for non-college females than for college females. The number of children per woman has been roughly constant for the cohorts born after the 1950s for both education groups (but, perhaps, for a small increase in the number of children born among college educated females for the latest cohort in Figure 11). To evaluate changes

[22]We use IPUMS-CPS data (Ruggles et al. (2009)) on number of children in the household, earnings, weeks worked, and hours worked per week from the years 1962 to 2008. We group individuals in five-year cohorts denoted by the middle point (for instance cohort 1941 groups cohorts 1939 to 1943).

in human capital accumulation across cohorts of women, we compare the increase over the life-cycle in the gender wage gap for various cohorts. We measure the change in the gender wage gap between age 20 to age 40 for non-college females and between age 23 to age 40 for college women. The findings are presented in Figure 12, where the data is grouped so that each cohort comprises 5 years groups (labeled by the mid year). We find that from the earliest cohorts up to the 1951 cohort there is a steep decline in the gender wage gap for both education groups. Importantly, this decline coincides with a steep decline in the fertility rate (see Figure 12). For college women, the growth in the gender wage gap over the life-cycle declined by 16% points between the 1941 and 1951 cohorts, just as the number of children per college women declined by 0.35. Moreover, after the 1951 cohort, both the number of children and gender wage gap of college females are roughly constant. Regarding non-college females, the life-cycle increase of gender wage gap declined by 27% points between the 1941 and 1951 cohorts, just as the number of children per non-college female declined by 0.64. After the 1951 cohort, there was an important moderation of both the decline of the gender wage gap and the decline in the fertility rate of non-college women. Altogether, the evidence in Figures 11 and 12 clearly indicates that the bulk of the decrease in the gender wage gap occurred for the cohorts 1941 to 1951 and that the timing of this decline coincided with the largest decrease in fertiliy across cohorts.

We use our quantitative theory to evaluate how much changes in fertility behavior account for the variation in the gender wage gap between the cohorts born in 1941 and 1951. We focus on this period because the bulk of the decline in the gender wage gap documented in Figure 11 occurred for the cohorts born during the 1940s. We assume that the baseline economy represents the 1951 cohort and we simulate a change in fertility opportunities to mimic the fertility behavior of women from the 1941 cohort. In particular, we change fertility opportunities in the baseline economy so that the fertility rate increases by 0.64 for non-college females and 0.35 for college females and the average age at first birth decreases by 2 years for both education groups, which are the main changes in fertility behavior observed when moving backwards from the 1951 to the 1941 cohort (see Table 19). We find that the gender wage gap increases over the life-cycle by an extra 10 percentage points for non-college individuals and by an additional 7 percentage points for college individuals, which should be compared to the changes of 27 and 16 percentage points for non-college and college individuals in the data (see Table 18). Hence, changes in fertility behavior account for 37% and 44% of the change in the gender wage gap observed for non-college and college individuals between the 1941 and 1951 cohorts.

Table 18: Trends: The Gender Wage Gap and Fertility

Change between cohorts 1941 to 1951:	Non-College	College
Number of Children	-0.64	-0.35
Age at First Birth	+2 years	+2years
Lifecycle increase of gender wage gap	-0.27	-0.16
Employment Mothers of young children	+0.20	+0.25

Data source: Own calculations from IPUMS-CPS data.

Table 19: Experiment 1: 1941 versus 1951

Change relative to benchmark:	Non-College	College
Number of Children	+0.64	+0.35
Age at First Birth	-2 years	-2years
Lifecycle increase of gender wage gap	+0.10	+0.07
Employment Mothers of young children	-0.09	-0.09

Our quantitative findings in Table 19 point that changes in fertility behavior account for an important fraction (about 40%) of the changes in the gender wage gap across cohorts born during the 1940s. Nonetheless, at first sight, the data for college women for the evolution of the gender wage gap for the cohorts 1946 to 1951 seems puzzling: The life-cycle increase in the gender wage gap was reduced by 9 percentage points across these cohorts while the fertility rate changed by a small amount (a reduction of 0.05 children). What can account for the higher wage growth of females in the 1951 cohort relative to the 1946 cohort? We now to show that a change in the timing of births may have played an important role. While the fertility rate of college women was roughly constant across the 1946 to 1951 cohorts, the average age of mothers at first birth increased by one year. Motivated by this observation, we use our quantitative theory to simulate an increase in one year of the average age of mothers at first birth. We find that the gender wage gap over the life-cycle rises by an extra 3.5% points. Hence, as in our previous experiment, the change in fertility behavior -a delay in the timing of births- accounts for about 40% of the change in the gender wage gap across the 1946 to 1951 cohorts.

Discussion Our findings complement some recent papers analyzing trends in women labor-force participation and wages. Olivetti (2006) and Buttet and Schoonbroodt (2006) argue that the increase in female labor force participation over recent cohorts could be explained by an upward shift in the returns to experience faced by females. While it is not obvious what could be the source of such a shift in the returns to experience, our paper contributes to this literature by showing that a decrease in fertility can lead to both an increase in the labor force participation of women and to an increase in the return to experience faced by women. In a closely related paper, Attanasio et al. (2008) emphasize that there was a large increase in the labor market participation rate of mothers with young children between the cohorts born in the 1940s and in the 1950s. This increase was about 20% points for non-college famles and 25% points for college females (see Table 18). Using a quantitative theory of female labor supply decisions, Attanassio et al. (2008) find that the decrease in the child care cost experienced by women born in the 1950s accounts for an increase in the employment rate of mothers of 14 percentage points. Our results in Table 19 complement the findings of Attanasio et al. (2008) by showing that changes in the fertility behavior across the 1941 to 1951 cohorts account for an increase of 9 percentage points in the employment rate of young mothers. Thus, it appears that changes in fertility and child care costs could account for most of the dramatic increase in the labor supply of young mothers.

7 Conclusions

This paper measures how much of the gender wage gap over the life cycle is due to the fact that working hours are lower for women than for men. Building detail labor market histories of men and women from NLSY data, we document large differences in labor supply: By age 40 the gender differences in cumulative hours of work are 45% among non-college and 27% among college individuals. We build a quantitative theory of fertility, labor supply, and human capital accumulation decisions to measure gender differences in human capital investments over the life cycle. The human capital technology is calibrated using wage-age profiles of men. While females are assumed to be identical to males in terms of the human capital technology, we assume that the bearing and presence of children involves a forced reduction in hours of work that falls on females rather than on males and that there is an exogenous gender gap in hours of work. The model is calibrated to the fertility patterns and the impact of children on female labor hours in the data. The calibrated model economy is used to measure human capital investments of females during the life cycle. We find that our theory accounts for all of the increase in the gender wage gap over the life cycle in the NLSY79 data. The impact of children on the labor supply of females accounts for 56% and 45% of the increase in the gender wage gap among non-college and college females, whereas the remaining part is due to the assumed exogenous gender differences in labor supply.

We use data on black non-college individuals from the NLSY79 -with the oversample of blacks- and time series data from the CPS to test the predictions of the theory. Consistently with our theory, the data reveals that black non-college women give birth to more children, work less hours, and accumulate less human capital than the average non-college women in the population. In a quantitative experiment we find that racial differences in fertility behavior account for 44% of the differences in life cycle wage growth between black non-college women and the average non-college women in the NLSY79 data. The time series evidence from the CPS indicates that changes in fertility behavior account for the evolution of the gender wage gap across cohorts -both the decline and the timing of the decline. The biggest decline in the gender wage gap occurred between the cohorts of women born in 1941 and 1951 and our quantitative experiments indicate that changes in fertility behavior account for 37% and 44% of the observed changes in the gender wage gap for non-college and college individuals.

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8 Appendix

Table 20: Parameter Values

Non-College				College			
Parameter	Value	Parameter	Value	Parameter	Value	Parameter	Value
v_{17}	8.0	$\triangle$	3%	v_{20}	35.10	$\triangle$	4.15%
v_{20}	1.12	α_1	0.351	v_{21}	5.0	α_1	-0.31
v_{25}	0.42	α_2	0.379	v_{23}	0.35	α_2	0.457
v_{30}	0.29	$\theta^{17-21}(0)$	0.0269	v_{25}	0.38	$\theta^{20-24}(0)$	0.0082
v_{40}	0.25	$\theta^{22-26}(0)$	0.0265	v_{30}	0.07	$\theta^{25-29}(0)$	0.0210
v_{50}	0.24	$\theta^{27-31}(0)$	0.0265	v_{40}	0.05	$\theta^{30-34}(0)$	0.0259
v_{55}	0.25	$\theta^{32-40}(0)$	0.0090	v_{50}	0.05	$\theta^{35-40}(0)$	0.0086
v_{60}	0.34	$\theta^j(1)$	$\theta^j(0) * 1.44$	v_{60}	0.20	$\theta^j(1)$	$\theta^j(0) * 2.66$
v_{65}	1.6	$\theta^j(2)$	$\theta^j(0) * 0.76$	v_{65}	0.86	$\theta^j(2)$	$\theta^j(0) * 0.76$
ρ	0.76	$\theta^j(3+)$	$\theta^j(0) * 0.76$	ρ	0.76	$\theta^j(3+)$	$\theta^j(0) * 1.27$
σ_ϵ	0.79	μ_{v_c}	0.7	σ_ϵ	1.345	μ_{v_c}	4.1
$\sigma_{h_{17}}$	0.233	γ_n	1.0	$\sigma_{h_{20}}$	0.395	γ_n	1.0
γ_h	0.728			γ_h	0.976		

Table 21: Race Experiment: Parameter Values

Parameter	Value
$\theta^{17-21}(0)$	0.0415
$\theta^{22-26}(0)$	0.0260
$\theta^{27-31}(0)$	0.0237
$\theta^{32-40}(0)$	0.0044
$\theta^{j}(1)$	$\theta^{j}(0) * 1.62$
$\theta^{j}(2)$	$\theta^{j}(0) * 1.167$
$\theta^{j}(3+)$	$\theta^{j}(0) * 1.06$
μ_{v_c}	0.65

Table 22: Race Experiment: Employment Ratio of Mothers by Age of Youngest Child

Age of Child:	Data	Model
1 quarter	24	25
2 quarter	34	33
3 quarter	38	37
4 quarter	40	40
[1, 5) years	49	56
[5, 6) years	60	74

Table 23: Race Experiment: Fertility Rate, Birth Rates by Age, and Distribution of Females at Age 40 by Number of Children

	Data	Model
Average Fertility	2.28	2.28
Birth Rates by Age: (%)		
17-19	27	24
20-24	32.4	34
25-29	22.5	24
30-34	12.6	11
35-40	5.5	6.6
Female Distribution by Number of Children: (%)		
0	12	13
1	15	14
2	31	27
3	23	24
$\geq$4	19	22

Table 24: Trends Experiments: Parameter Values

Experiment 1

Non-College		College	
$\hat{\theta}^j(0)$	$= 2.2 * \theta^j(0)$	$\hat{\theta}^j(0)$	$= 2.3 * \theta^j(0)$
$\hat{\theta}^j(1)$	$= 1.37 * \theta^j(1)$	$\hat{\theta}^j(1)$	$= 0.5 * \theta^j(1)$

Experiment 2: College

$\hat{\theta}^j(0) = 1.6 * \theta^j(0)$
$\hat{\theta}^j(1) = 0.38 * \theta^j(1)$

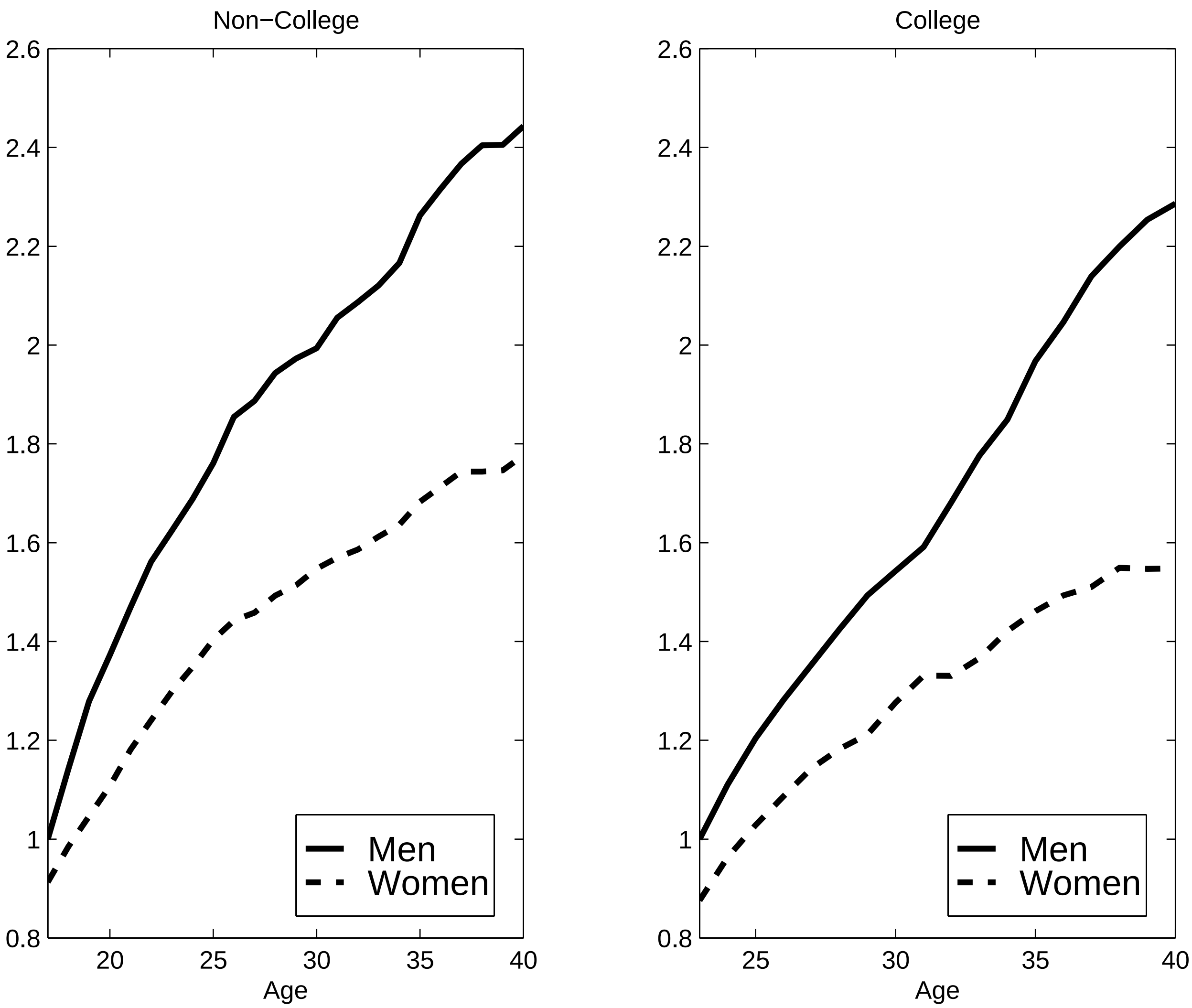
θ^j and $\hat{\theta}^j$ denote the fertility opportunity of the baseline calibration and experiment, respectively.

Table 25: Trends Experiments: Fertility, Employment of Mothers, and Wage Growth

	Non-College		College		
	Benchmark	Experiment 1	Benchmark	Experiment 1	Experiment 2
Average Fertility	1.95	2.59	1.55	1.89	1.56
Age at first birth	22.5	20.0	27.9	25.9	26.9
Employment mothers					
of children less than 3	0.62	0.54	0.75	0.67	0.70
$\triangle$ gender wage gap					
over the life cycle	0.25	0.34	0.22	0.30	0.26
Wage Growth Males	2.03	2.03	2.28	2.28	2.28
Wage Growth Females	1.52	1.33	1.77	1.60	1.69

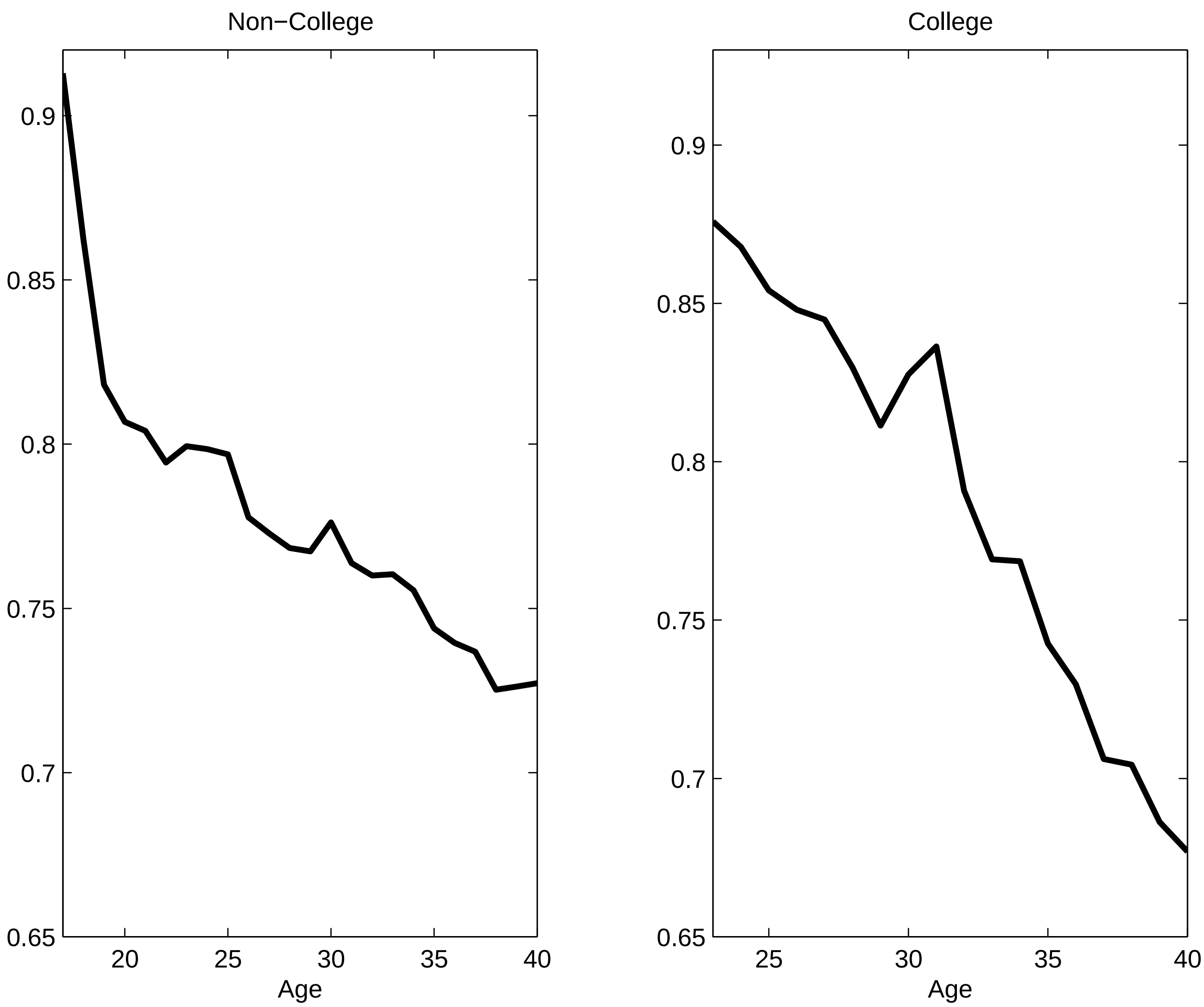
The increase in the gender wage gap and wage growth are computed between ages 20 and 40 for Non-college and 23 and 40 for College.

Figure 1: Average Hourly Wage by Age



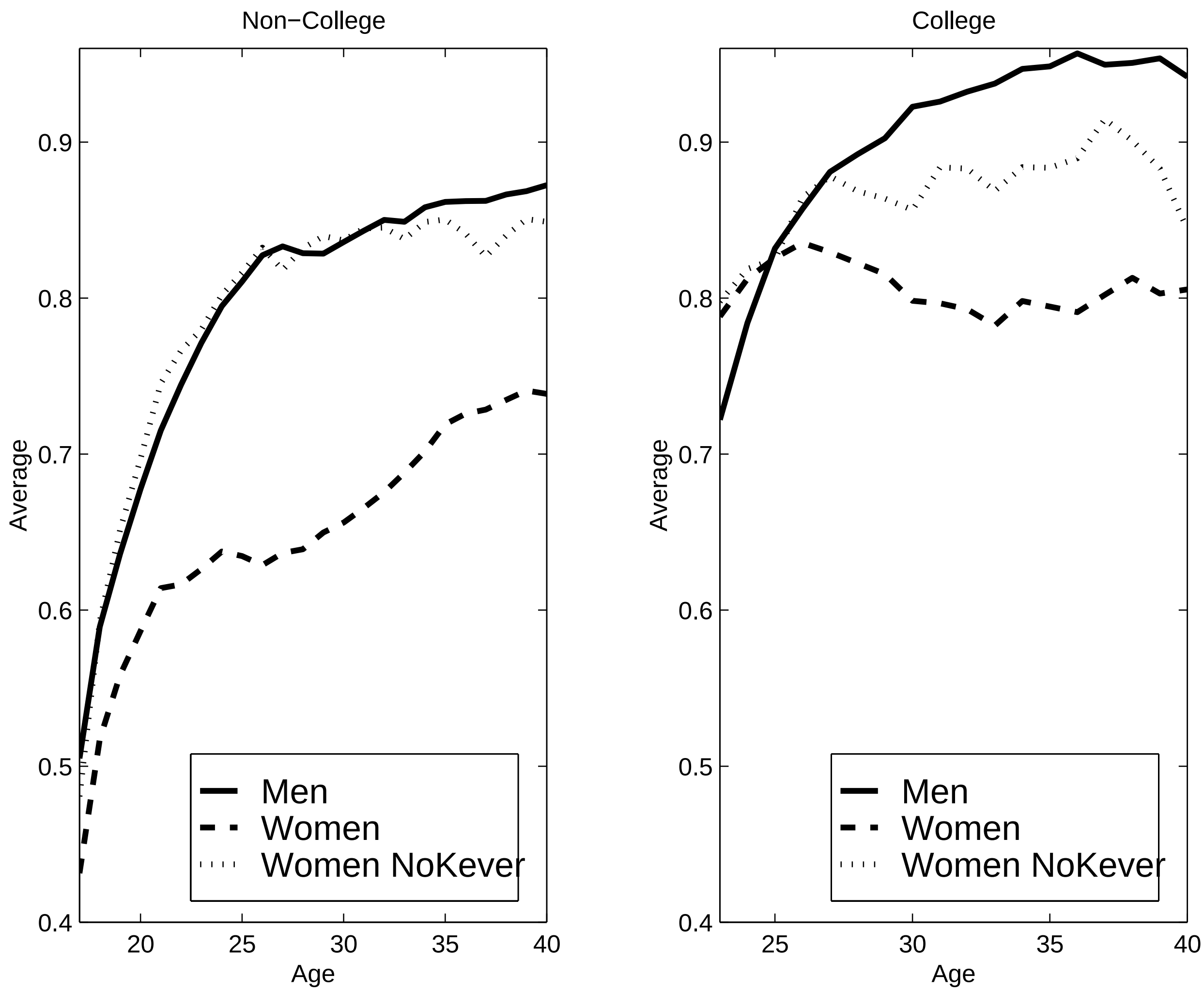
Relative to the average wage of men at age 20.

Figure 2: Gender Wage Ratio by Age



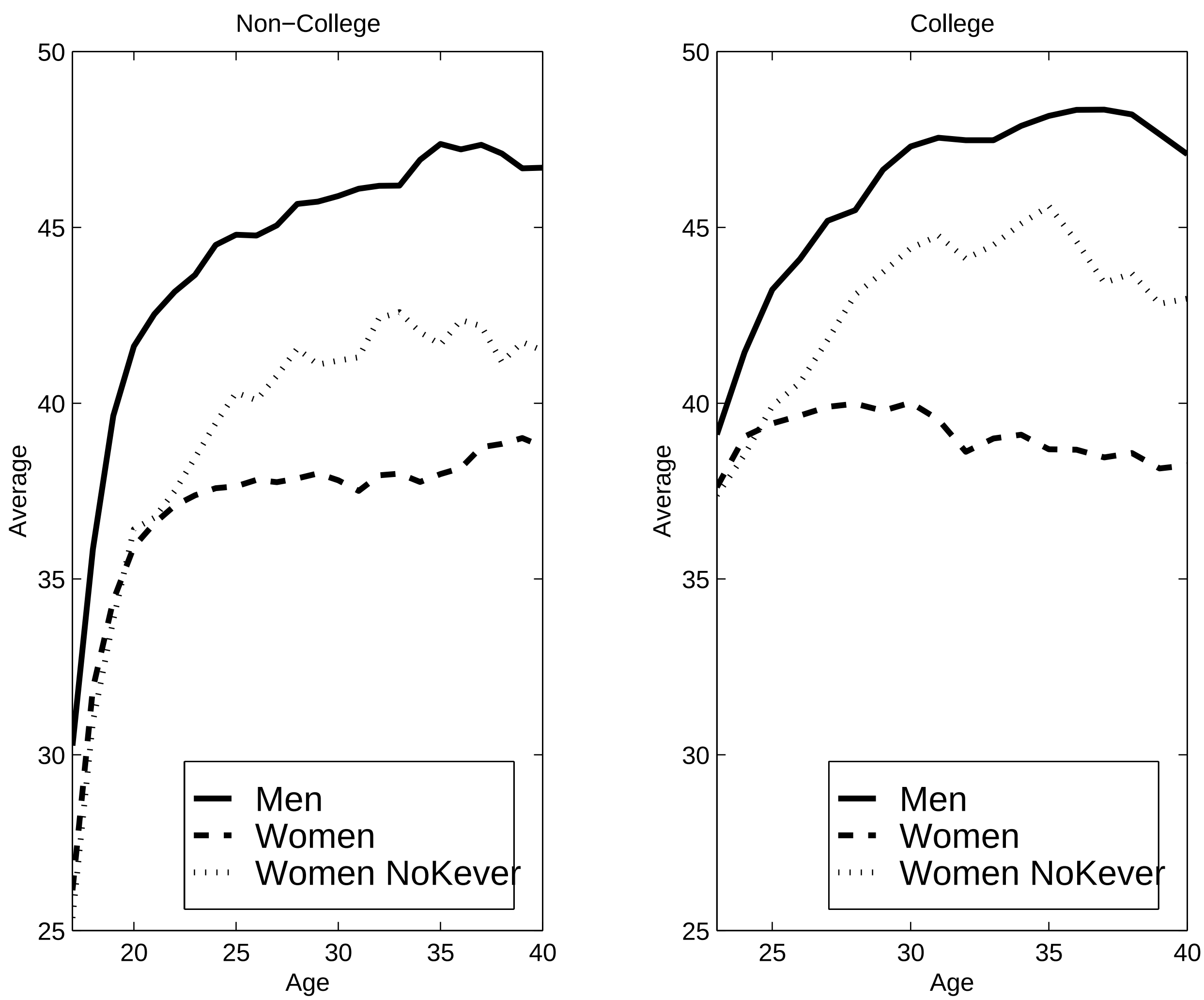
Average wage of women relative to males at each age.

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 rate around birth

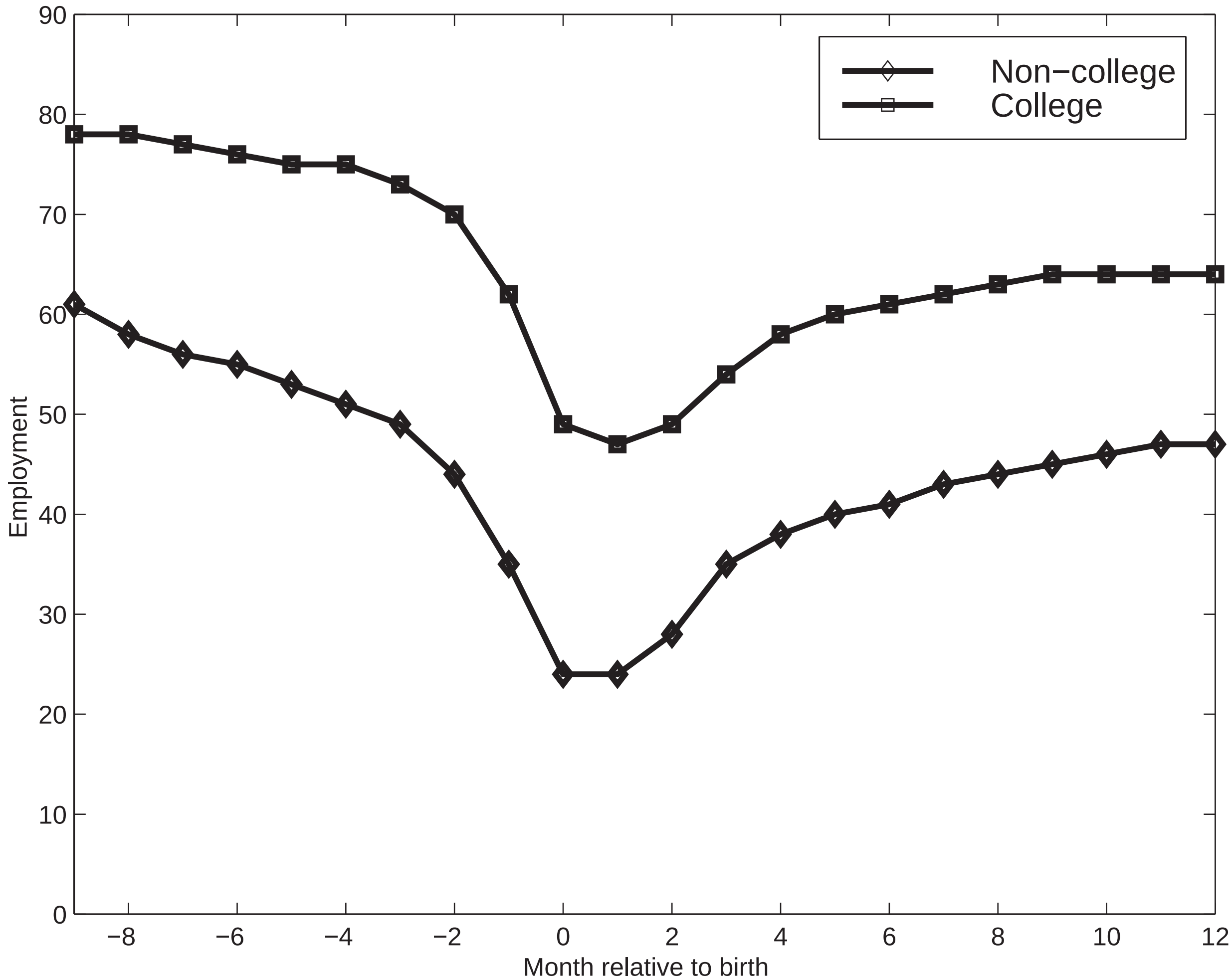


Figure 6: Employment rate

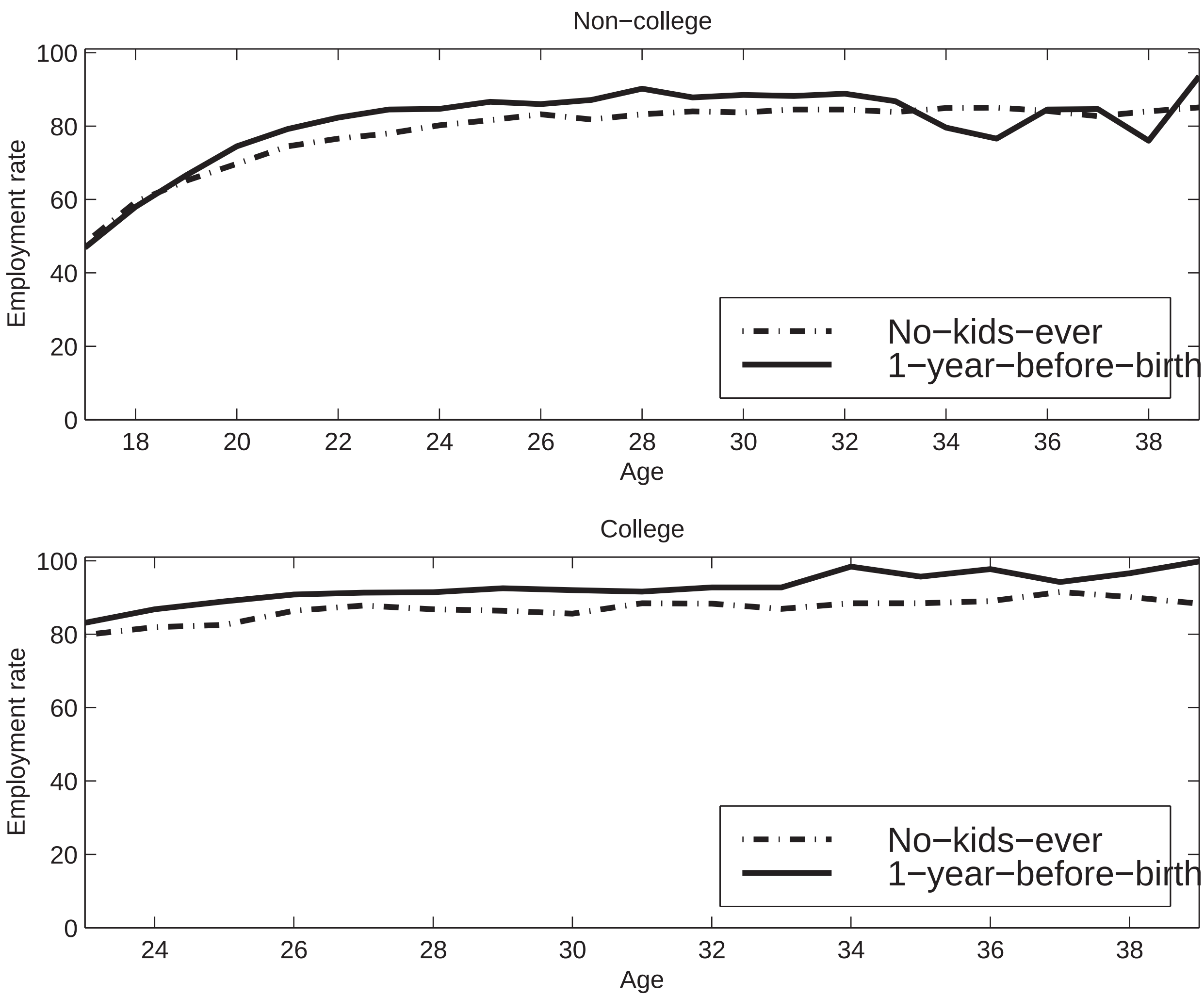


Figure 7: Hours per week

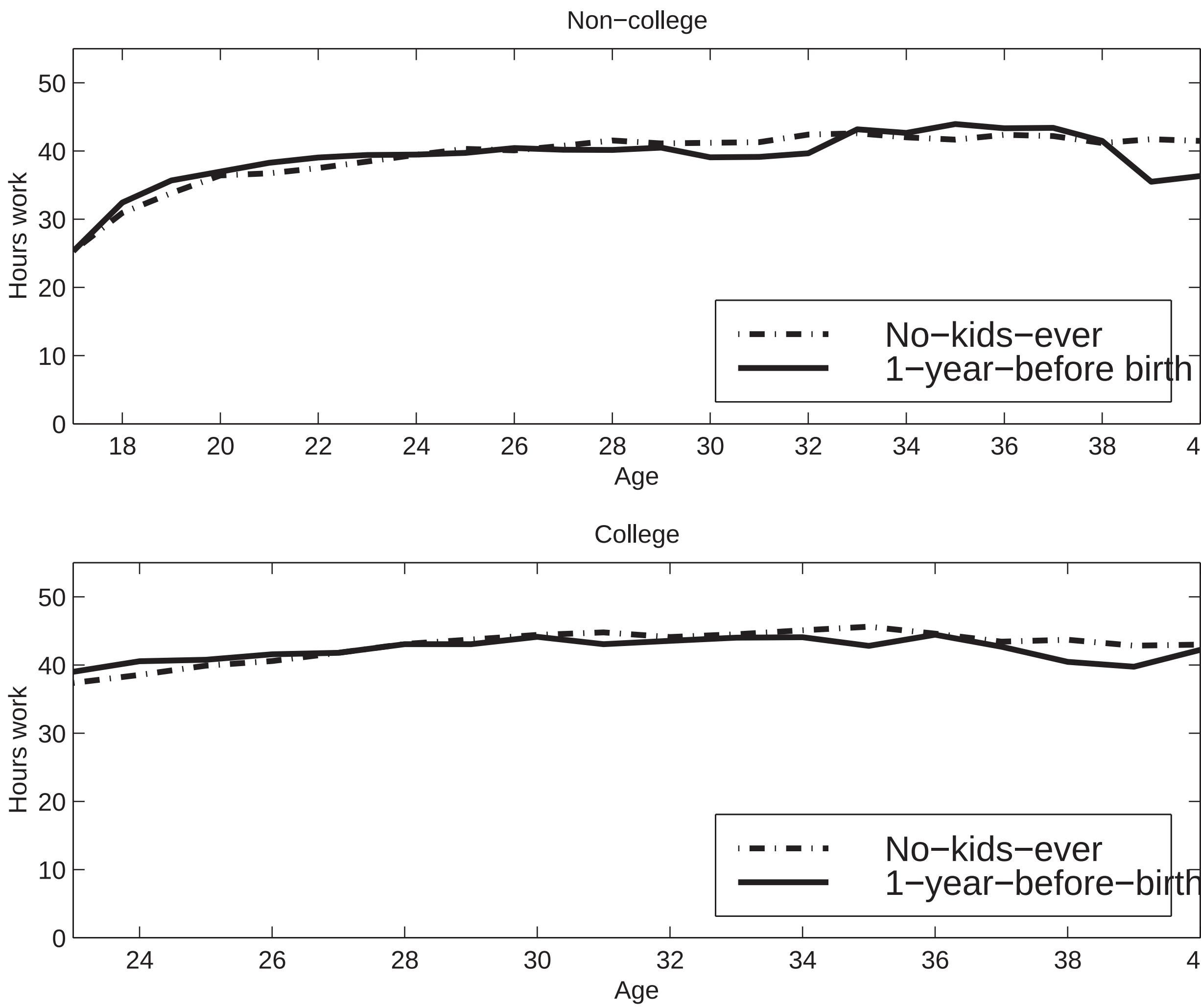


Figure 8: Employment Ratio by Age -Males

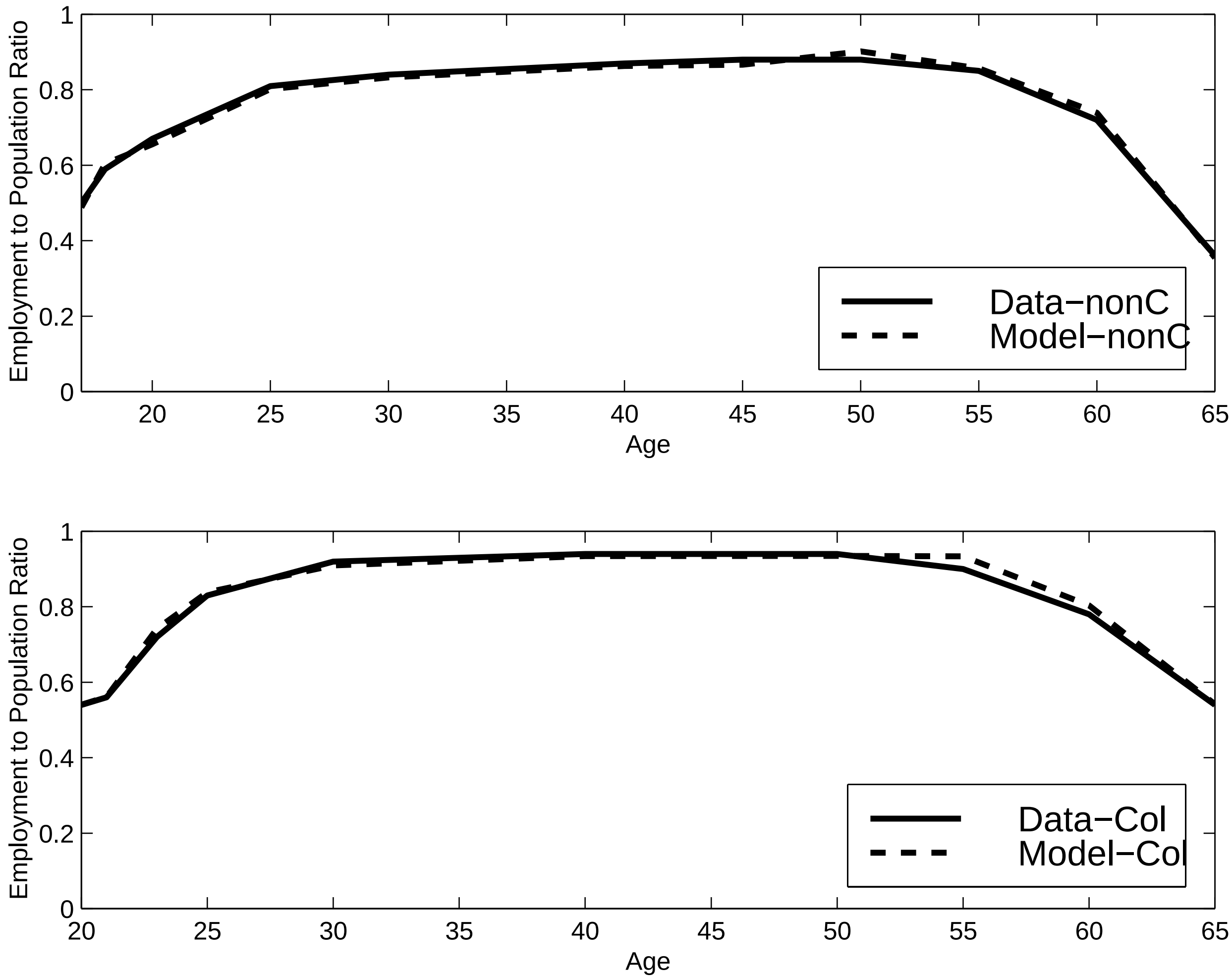
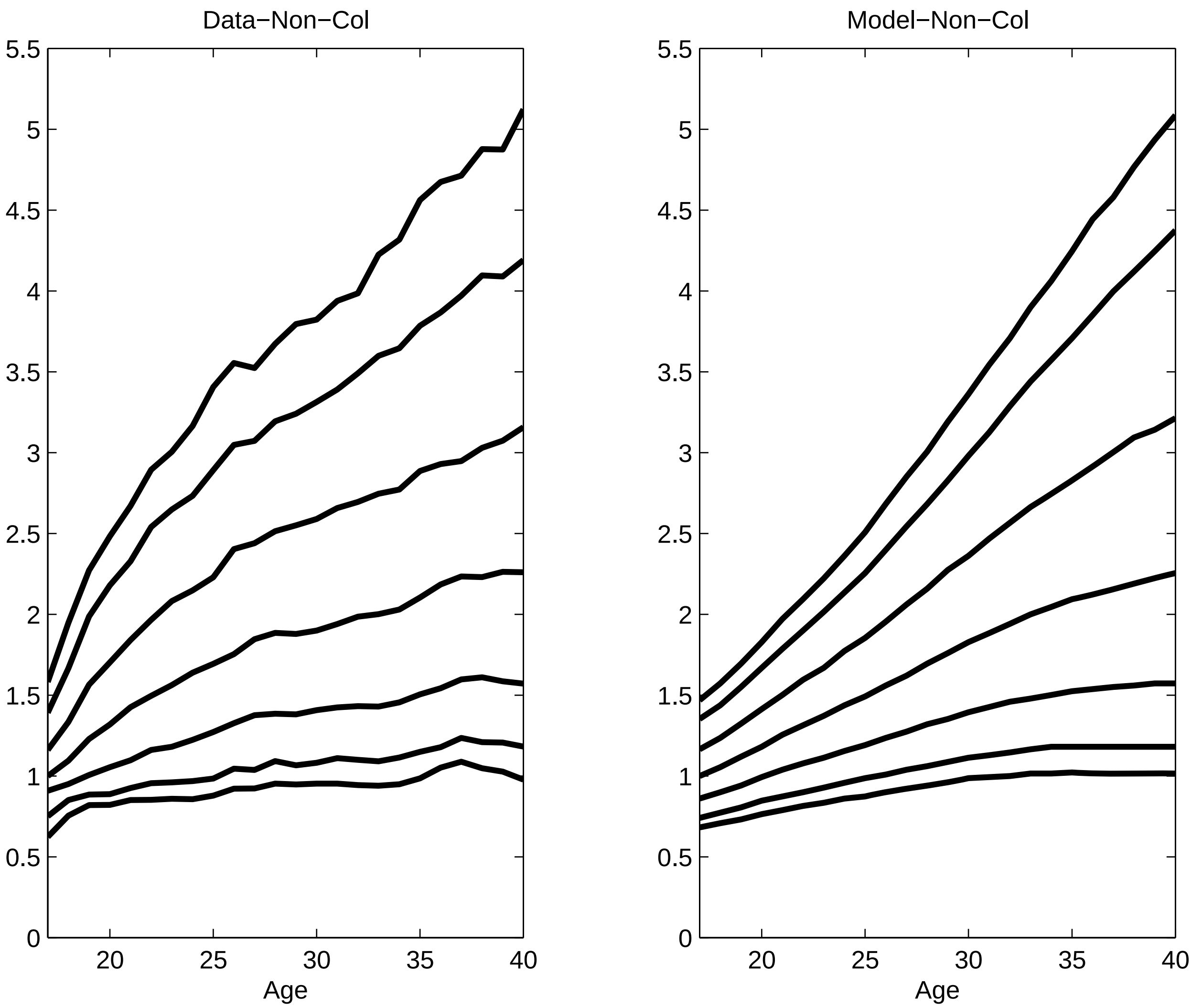
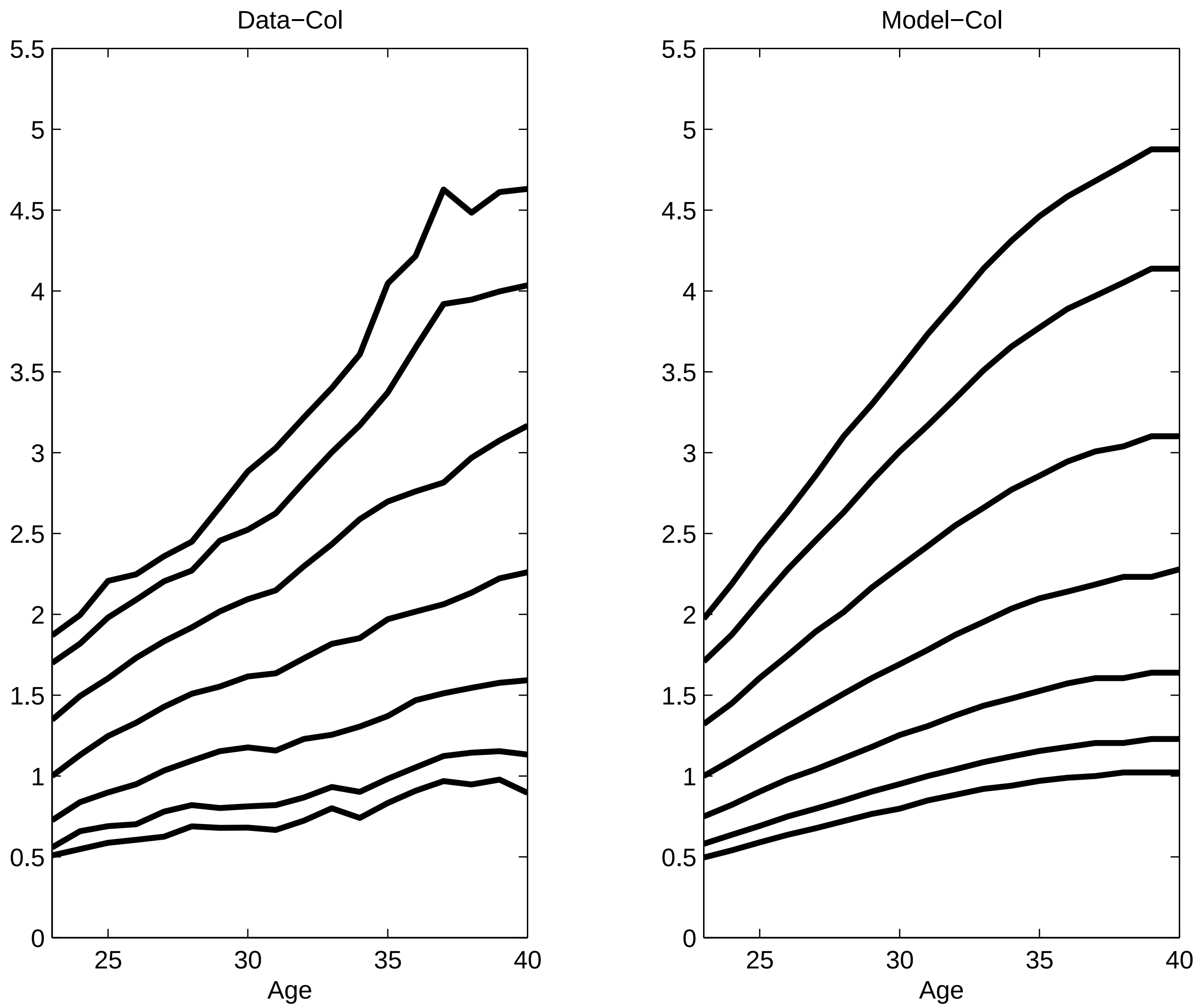


Figure 9: Age Profile of Wages - Non-College Males



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 - College 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 11: Number of Children by Cohort

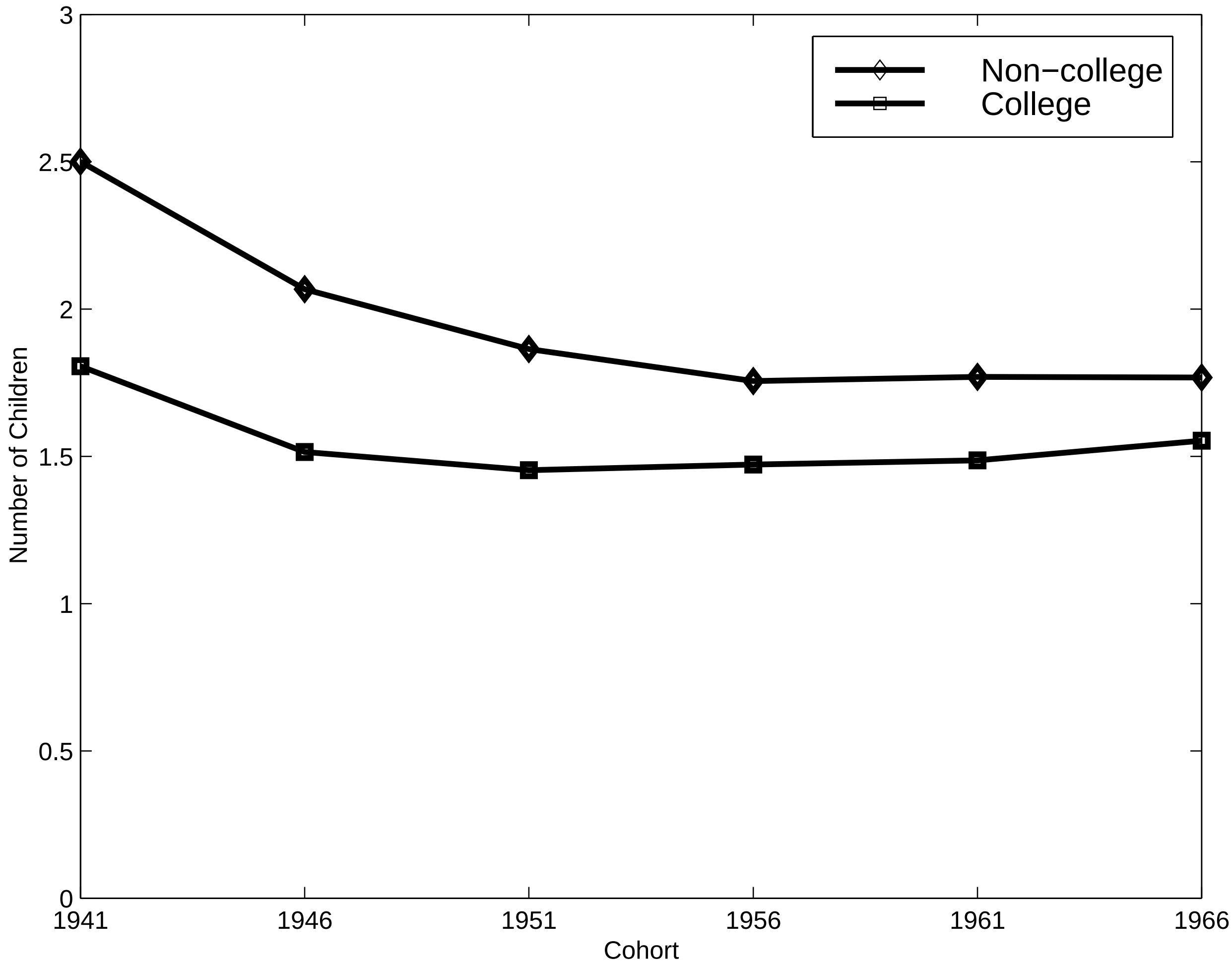


Figure 12: Lifecycle increase of Gender Wage Gap by Cohort