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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 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. 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 females, while the rest is due to the exogenous gender differences in hours of work.

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1. Introduction

A striking but well-known feature of the US labor market is that the average hourly wage of women is much lower than that of men and that women face lower wage growth over the life cycle than men. A large empirical literature is aimed at understanding the sources of gender difference in wages. Empirical studies typically find that males earn higher wages (even after controlling for gender differences in observed characteristics) and face higher returns to labor market experience than females.[1] One problem in interpreting these results is that we cannot assess to what extent they are driven by (unobserved) investments in human capital. Economic theory suggests that this is a difficult problem to deal with. Since the return to human capital accumulation depends on future labor supply, theory implies that investments should be driven by expected labor supply (rather than by past labor supply). While economic theory prescribes that investment decisions are forward looking, obvious data limitations make it hard to incorporate labor supply expectations into the empirical analysis.

In the present paper, we use quantitative theory to assess the importance of (unmeasured) human capital investments in understanding gender differences in wage growth over the life cycle. In our theory, individuals decide how much (unobserved) effort to spend in accumulating on the job human capital and whether to work or stay at home. We assume that females also make fertility decisions. 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 involves a forced reduction in hours of work that falls on females rather than on males and

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[1] See, for instance, Blau and Kahn (1997, 2000).

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that there is an exogenous gender gap in hours of work. 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 and to compare it with that of males.[2]

The starting point of our analysis is that there are substantial gender differences in labor supply in the United States. Using data from the NLSY(1979) we build detailed labor market histories of men and women and add 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 (notice 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).[3] 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.[4] Human capital theory implies that gender differences in hours of work should translate into different incentives for human capital accumulation across genders. Furthermore, the data lends supports to the importance of human capital investments as determinants 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, the data suggests that differential investments in human capital can be large since over the first 20 years of labor market experience men's wages grow one percentage point higher per year than women's wages.

Our quantitative theory is built to match the males' age–employment profile and the age-profile of hours of work for college and non-college individuals. Regarding females, the theory replicates the birth rates by age and the impact of children on career interruptions and labor supply for college and non-college females. 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. 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.

Our findings are consistent with the vast empirical literature that finds a substantial gender residual in wage regressions that measure human capital investments by past experience. To illustrate this point, we simulate non-college educated males and females in our model that are identical in terms of initial human capital and lifetime employment. Our simulated males and females only differ in lifetime labor supply because females work 10% less hours than males and because females expect to have children – with the associated negative impact on labor supply – even though ex-post no female is ever given an opportunity to have children. Since females in this experiment work more than 35 hours a week, we follow the empirical literature in counting them as full-time employed. Hence, the data generated by this experiment features no gender differences in experience as measured by full-time employment. Nevertheless, we find a gender wage ratio of 0.875 at age 40. Using the simulated data, a standard wage regression of log wages on experience (measured as full-time employment) and a sex dummy as explanatory variables, would attribute a negative wage effect to being a female worker and a lower return to (measured) experience by females relative to males. We conclude that, in the context of our model, standard measures of experience typically used in the empirical literature are not good measures of investment in human capital over the life cycle.

Our paper is motivated by some basic insights from human capital theory. 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).[5] These authors provide evidence that married women tend to interrupt their labor market attachment with periods of non-participation and, using a regression

[2] Our model assumes that women start their life cycle with the same human capital as males (at 17 years of age for non-college and 23 years of age for college women). Hence, our theory abstracts from the initial gender wage gap of about 10% in the data. However, we emphasize that by age 40 the bulk of the gender wage gap (about 70%) is explained by gender differences in wage growth over the life cycle. Moreover, note that the forces that imply low employment and hours of work by 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 the initial age in our model economy.

[3] 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 working hours, even among full-time workers.

[4] 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.

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

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 (1987) 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.

Our paper follows a research line in quantitative theory on the economics of the family initiated by Aiyagari et al. (2000) and Regalia and Ríos-Rull (1998). It is related to a recent macroeconomic literature that studies change in female labor supply over time; see Attanasio et al. (2008), Buttet and Schoonbrodt (2013), Cardia and Gomme (2013), Da Rocha and Fuster (2006), Domeij and Klein (2013), Greenwood and Guner (2009), Greenwood et al. (2005), Jones et al. (2003), Knowles (2009, 2013), and Olivetti (2006). Guner et al. (2012) analyze how taxation affects labor force participation of women and the returns to experience faced by females. Our paper follows Huggett et al. (2006, 2011) in using panel data on males 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. 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. 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 (2009) 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.

Our paper also relates to the literature on wage differences between mothers and non-mothers (see for instance Anderson et al., 2002; Skirbekk, 2003). Empirical studies in this literature emphasize the importance of children on work interruptions of women through destruction of firm-specific skills and good quality job matches. Erosa et al. (2002, 2010) argue that these features can account for only about 10–20% 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 that motivate our analysis. In Section 3, we describe the economic environment and in Section 4, we discuss the calibration. In Section 5, we present the main quantitative results and in the last section we conclude.

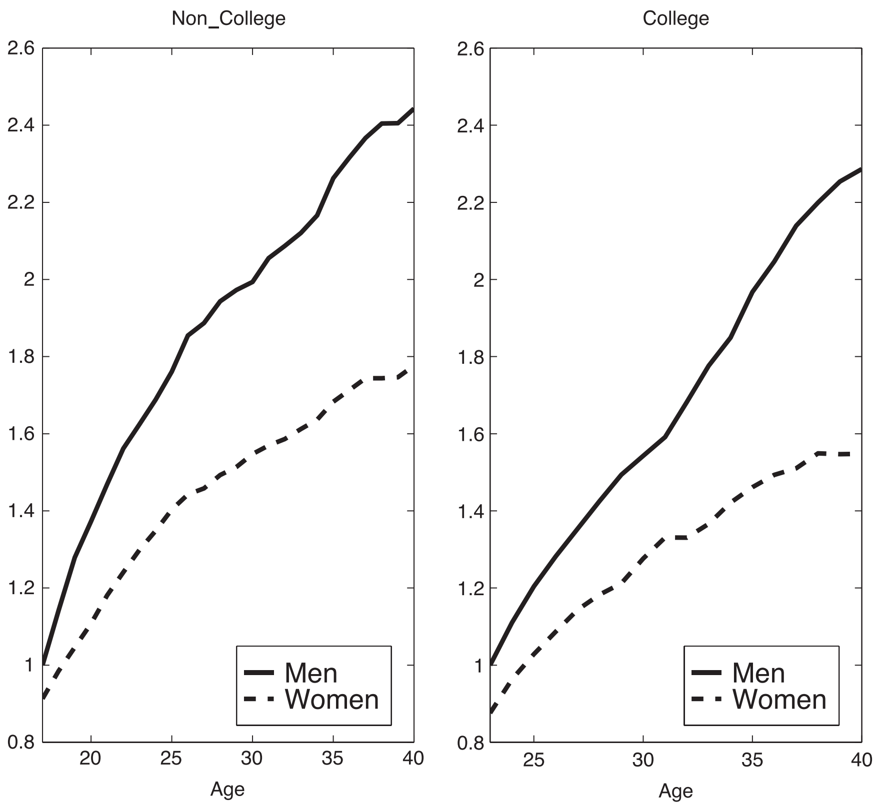


Fig. 1. Average hourly wage by age. Relative to the average wage of men at age 20.

Table 1
Average hours and employment.

Hours and employment	Non-college[a]			College[b]		
	Men	Women		Men	Women	
		All	No child[c]		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

[a] People 20–43 years of age.
[b] People 23–43 years of age.
[c] No child refers to women with no children (until the last observation in our sample, when women are 36–43 years old).

2. Data

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

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

Gender differences in wages: A salient feature of the labor market is that the average hourly wage of women is substantially lower than the average wage of men. In our sample of the NLSY79, the average wage ratio between women and men is 0.78. Although wages grow substantially over the life cycle for both men and women, the gender wage ratio decreases over the life cycle – the gender gap in wages increases with age. The increase in the average wage over the life cycle for men and women for both educational types is shown in Fig. 1. Whereas the average wage of non-college individuals increases between age 17 and 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 and 40 of about 20 percentage points. For people with college education, the average wage between age 23 and 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 and 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 h 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).[6] 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.

Figs. 2 and 3 document the life-cycle path of average hours per-worker and the employment to population ratio for men and women for both educational types. Among non-college, hours per worker and the employment to population ratio increase with age for both men and women, but employment is more prevalent for men than for women at every age group. While the employment to population ratio is about 7 percentage points higher for men than for women at age 17, by age 40 this difference is 13 percentage points. There is also a substantial gap in hours of work among people working: At age 17,

[6] 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 the working-age population, and W is the 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.

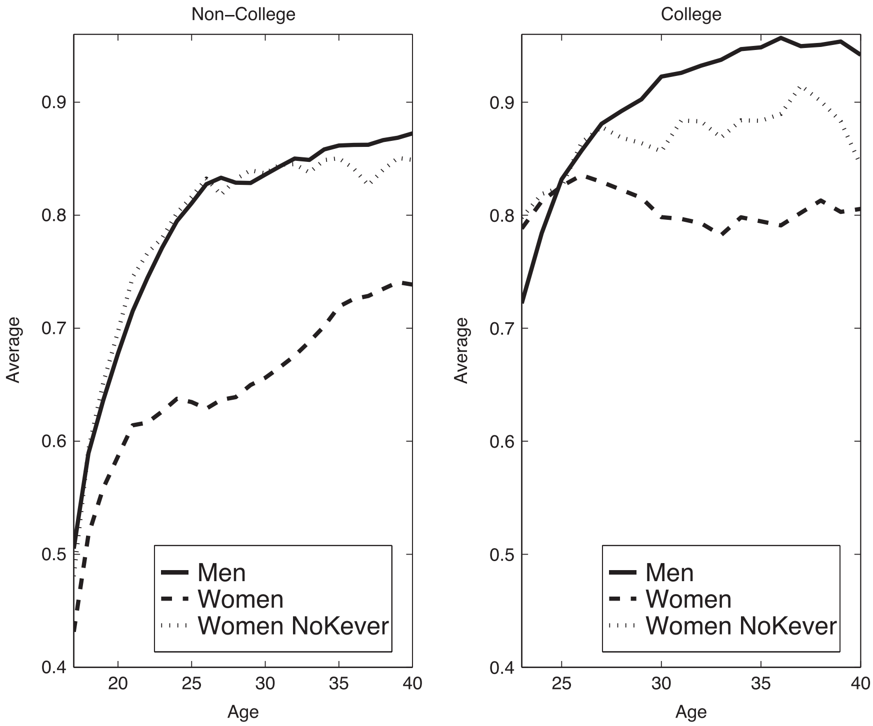


Fig. 2. Employment to population ratio. Women NoKever refers to women with no children (until the last observation in our sample, when women are between 36 and 43 years of age).

employed men spend 4 h more working per week than women. At age 40 the difference in hours of work is 9 h per week. Similarly, we find that the gender differences in hours worked and employment rate expand over the life-cycle for college educated individuals. Interestingly, we find that the employment rate and hours per worker of college educated women decrease with age during the child-rearing period.

Children and labor market outcomes: Labor supply differences across gender are substantial. What is striking in comparing labor market outcomes of men and women is the role that children play in labor supply decisions of women. We compare statistics for the average of all women and for the average of women who never had children.[7] 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 Fig. 2. 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 h per worker per week or about 10% of the hours per worker of males) (see Fig. 3). Among the college educated, we also observe that women with no children work more often and more hours than the average women.[8]

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 Fig. 2: gender differences in labor supply grow substantially at the ages when women start bearing children. While for non-college individuals the gender differences in employment rates grow substantially after age 23 and start diminishing rapidly before age 30, for college individuals the employment rate only differs across genders after age 26 and these differences are still substantial by age 40. These patterns are consistent with the fact that college educated women tend to give birth at older ages than less educated females and with the view that children – of young age – negatively affect the labor supply of mothers. 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 individuals and below 73% in the case of college women. The employment ratio of women with young children

[7] For the last observation of every woman in our sample – when they are between 36 and 43 years of age – we consider women who had not had children up to that point and we refer to them as women with no children (Women NoKever in the graphs).

[8] 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 the men (see Fig. 2). A possible explanation for the different behavior of women with no children across educational types is that college women marry wealthier men than non-college women.

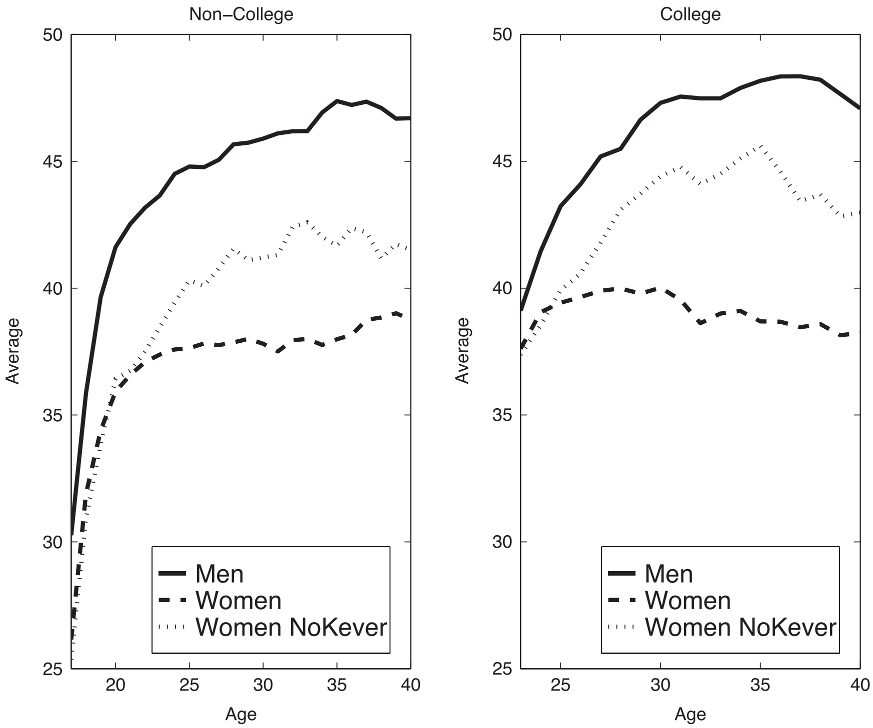


Fig. 3. Hours per-worker (per-week). Women NoKever refers to women with no children (until the last observation in our sample, when women are between 36 and 43 years of age).

Table 2
Average hours and employment.

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
3–6 months	14.0	34.8	40.0	19.7	34.2	57.8
6–9 months	15.1	34.6	43.8	20.7	33.9	61.1
9–12 months	15.7	34.8	45.2	21.1	33.9	62.4
1–5 years	19.4	36.1	53.8	24.0	34.8	69.0
5–6 years	23.7	37.4	63.5	27.7	36.1	75.7

(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 grows substantially with the age of their youngest children 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 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").[9] An important fraction of all non-employment spells do not involve the birth of a child (almost 82%) and the average duration of

[9] 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

Table 3
Duration of non-employment spells.

Duration	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

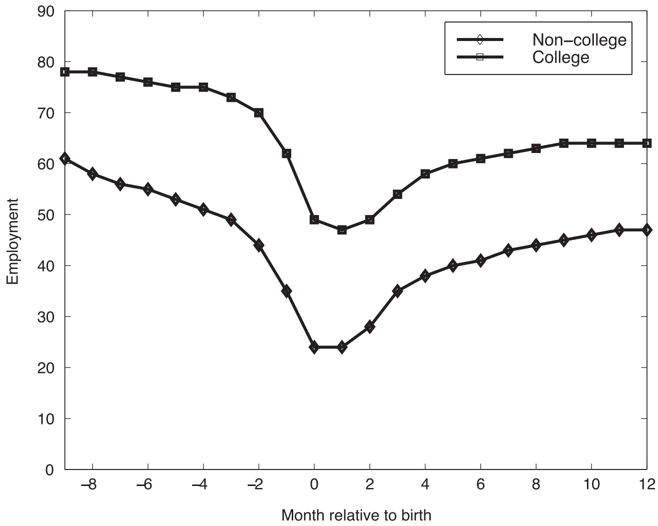


Fig. 4. Employment rate around birth.

these spells is similar to that of men (46 weeks for men vs. 50 weeks for women in the case of non-college and 42 weeks for men vs. 38 weeks for women in the case of college). Table 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.

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. Fig. 4 shows that the employment rate decreases during pregnancy and that it slowly recovers after childbirth. For both education groups, the employment rate one year after birth is still more than 10 percentage points below its level prior to pregnancy. 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.[10] 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. Fig. 5 compares the

(*footnote continued*)
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.

[10] While individuals might also differ in terms of cognitive ability, Cawley et al. (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.

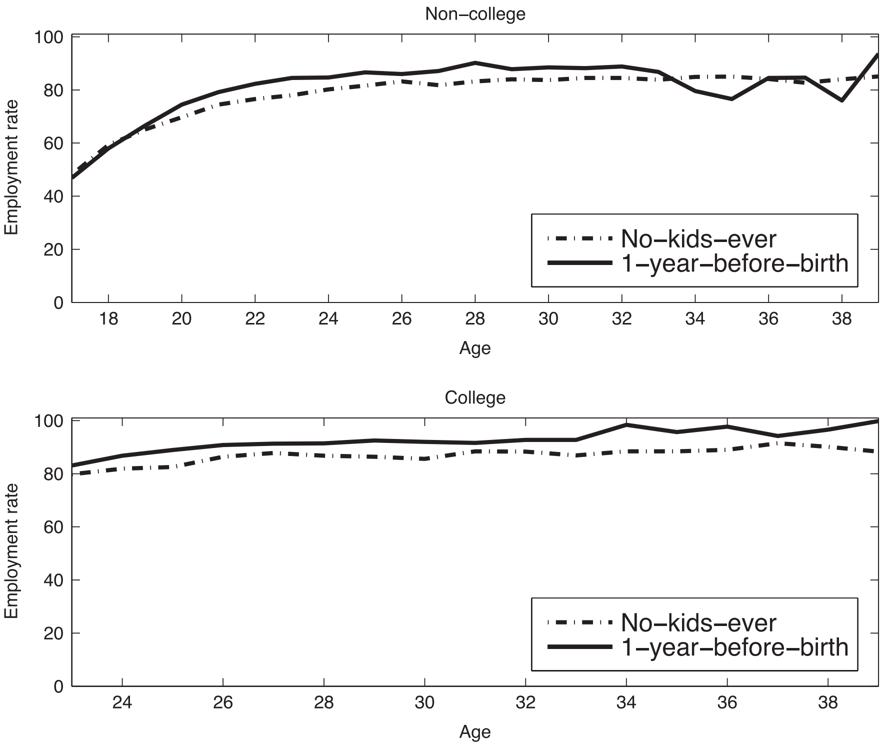


Fig. 5. Employment rate.

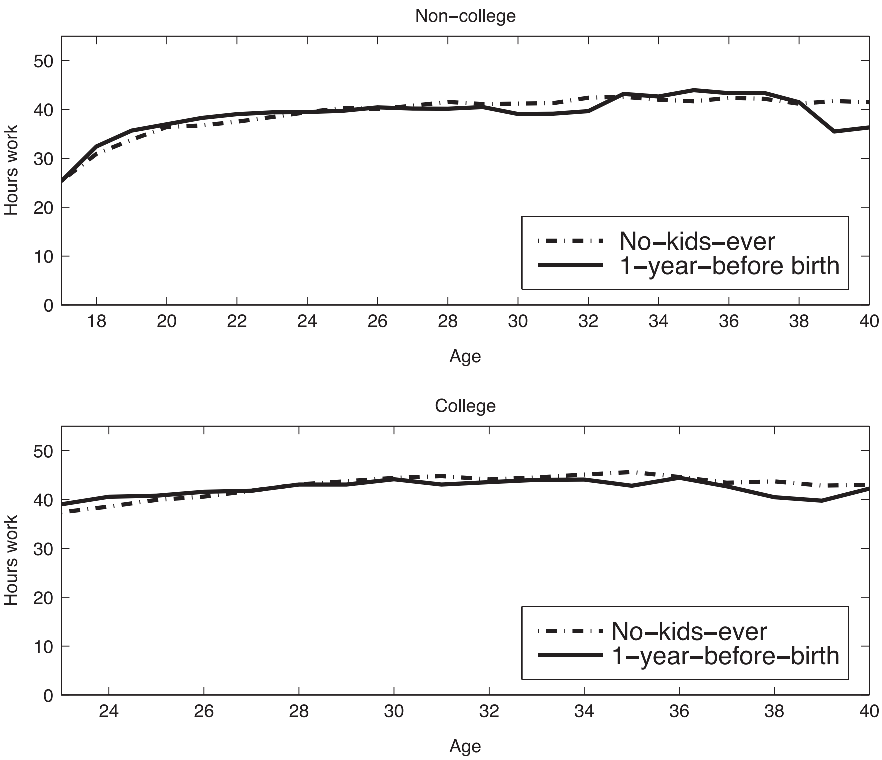


Fig. 6. Hours per week.

employment rate of women with no kids ever with the employment rate of mothers 1 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

Table 4
Accumulated experience at age 40 (years).

Experience	Non-college		College	
	Weeks	Hours[a]	Weeks	Hours[a]
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

[a] Refers to equivalent years corresponding to 52 weeks and 40 h of work per week.

women with no kids ever. Fig. 6 shows that average working hours, conditional on employment, are quite similar for women with no kids ever and for mothers one year before they gave birth to their first child. Altogether, the evidence in Figs 5 and 6 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 data from the National Longitudinal Survey 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, p. 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 of work and accumulated weekly hours of work.[11] 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.

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.[12] 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

[11] 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 that these cases as zero hours, but alternative assumptions yield similar results.

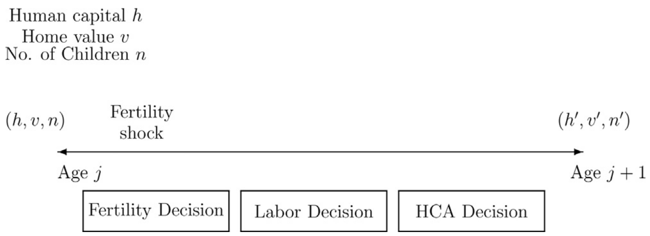
[12] Our theory can accommodate marriage by assuming that matching is independent of fertility, labor market, and human capital decisions. Extending the theory to model non-trivial joint decisions by husbands and wives is a daunting task since we would need to model three endogenous state variables (asset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

work, they earn labor earnings, which enter linearly in their utility function but they do not enjoy the entire utility of staying at home. The trade-off also has a dynamic component since we assume that human capital is accumulated while working.

Human capital accumulation decision: We model human capital accumulation while working. 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 Δ 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.[13] 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 make any decisions in this stage. In a second stage, people decide whether to work a fixed amount of hours (that depends on the age, gender, and number of children of the person) or not to work. In a third stage, working individuals decide how much effort to exert in accumulating human capital. People who do not work during the current period enjoy the value of staying at home. At the end of the period, individuals make a new draw for the value of staying at home (which is assumed to be correlated over time).



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

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

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

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

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

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

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 females' taste for children. If the worker exerts effort e, at a utility cost of $c(j,h)\log(1-e)$, the worker increases human capital to $h(1+\Delta)$ 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

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

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

(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 $u(h, v)$.

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 the life-cycle wage profile are important for setting the parameter that determine the technology of 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 from age 17 on since women between ages 17 and 19 account for 20% of all the births among women in this education group. College individuals are modeled from age 20 on. 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 had a first-order impact in the target. In the appendix, we report the calibrated parameter values for non-college and college individuals (see Table 18).

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 years of age are obtained from NLSY79 and for men 41–64 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 is 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. 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 Δ, 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

Table 6
Calibration for females.

Parameter	Target
$\theta^j(n)$	Distribution of number of children
γ_n	Total fertility rate
μ_{v_c}	Employment of mothers of a child younger than 1 year of age

Table 7
Fixed effects panel regression: hours worked by women.

Regressor	Non-college	College
Age	3.32	16.09
	(0.476)	(0.78)
Age^2	−0.086	−0.44
	(0.015)	(0.025)
Age^3	0.0007	0.0039
	(0.0001)	(0.0002)
Children	−6.81	−12.56
	(0.33)	(0.757)
Age∗children	0.133	0.239
	(0.009)	(0.020)
Intercept	0.196	−147.8
	(4.82)	(8.01)

the bottom and at the 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.[14]

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 the technology of human capital accumulation ($\Delta, \alpha_1, \alpha_2, \gamma_h$), and 1 parameter for the initial distribution of human capital σ_{h_0}. We proceed by minimizing a loss function which 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 the Appendix in Table 18.

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).[15] 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 the number of children. A summary of the parameters and the targets in the data is reported in Table 6. 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 who are mothers of a child younger than one year of age.

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 on average 10% less hours than males (at every age). We assume that the presence of children reduces the hours worked of mothers until they reach age 40 and that the reduction in hours depends on the age

[14] 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.

[15] 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.

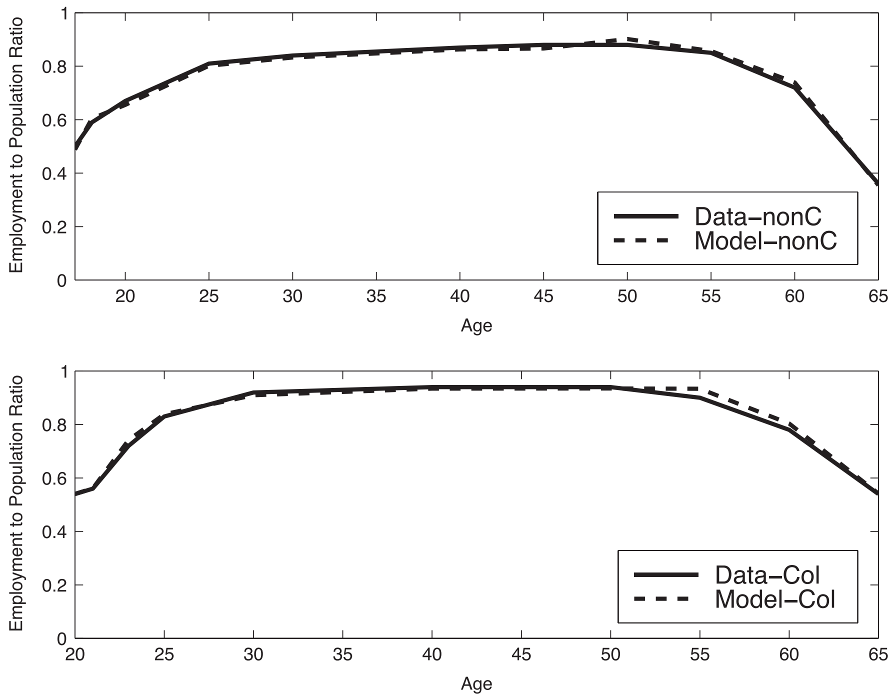


Fig. 7. Employment ratio by age – males.

Table 8
Distribution of accumulated experience (weeks) – males.

Experience	Non-college[a]		College[b]	
	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[c]	25.6[c]

[a] Between ages 17 and 40.
[b] Between ages 20 and 40.
[c] Between 19 and 21 years of experience.

of the mother.[16] 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 years 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 7. 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 h by the first birth and by 3.3 h by the second birth.[17]

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 the 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

[16] 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.

[17] Given that in the baseline economy college females have, on average, the first and the 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 h and 5.2 h for college females.

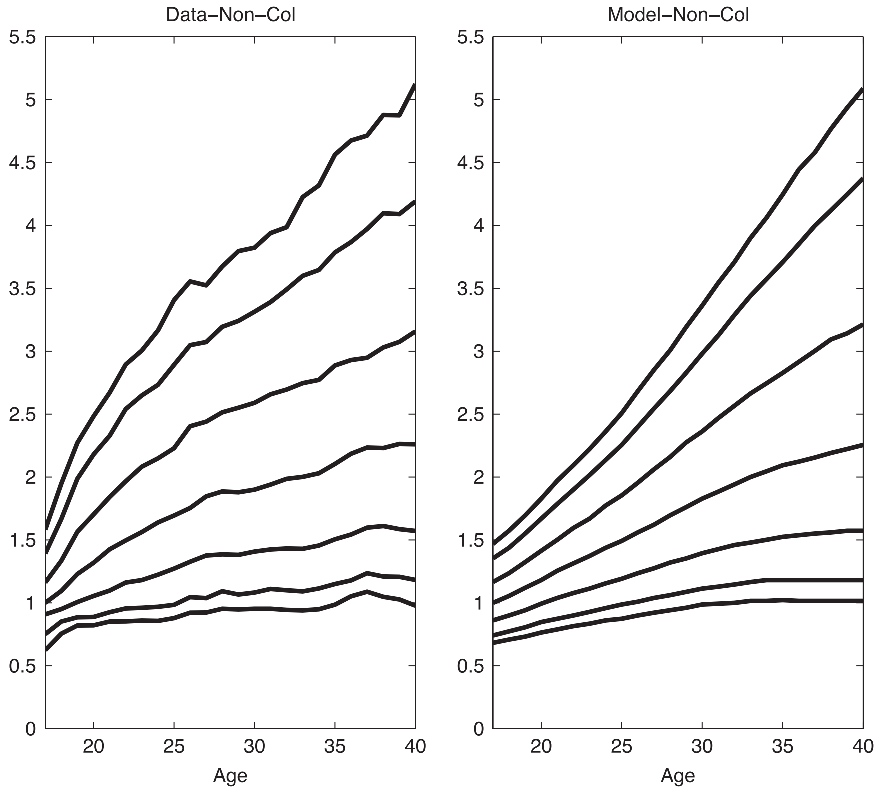


Fig. 8. Age Profile of wages – non-college males. The lines correspond to the following percentiles of the distribution of wages: 5, 10, 25, 50, 75, 90, and 95. Relative to the median wage of males at age 20.

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.

4.3. Calibration results

We now discuss how the model matches the calibration targets. Fig. 7 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 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 Figs. 8 and 9). 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% 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.

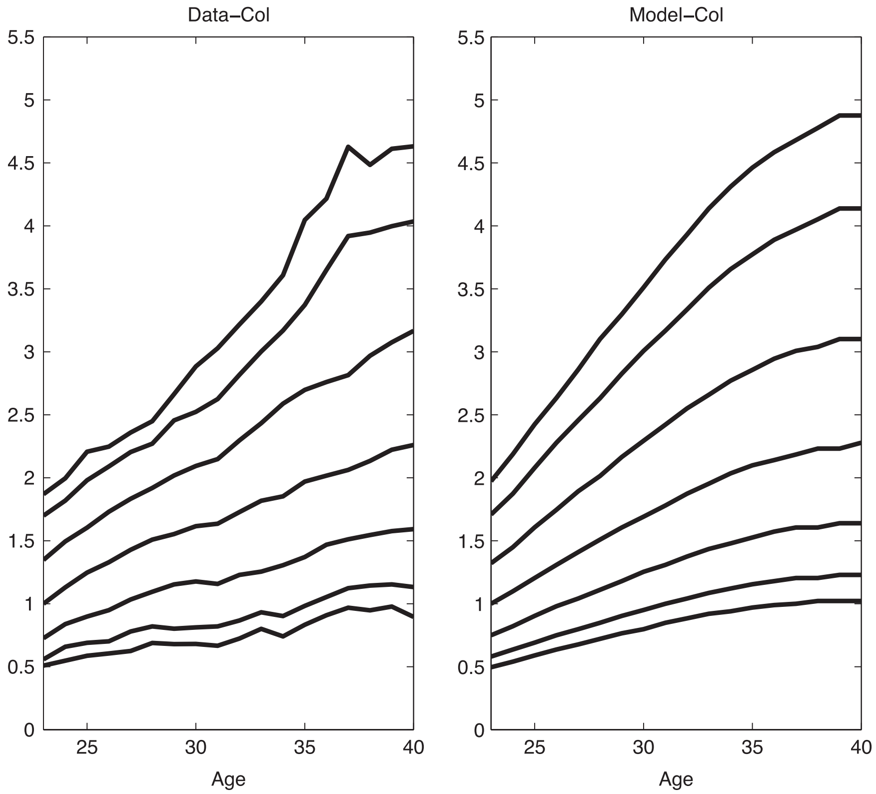


Fig. 9. Age profile of wages – college males. The lines correspond to the following percentiles of the distribution of wages: 5, 10, 25, 50, 75, 90, and 95. Relative to the median wage of males at age 20.

Table 9
Duration distribution of non-employment spells – duration weeks (%).

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

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

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

Table 12
Duration distribution of non-employment spells of mothers (%).

Duration (weeks)	Non-college[a]		College[b]	
	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

[a] Between ages 17 and 40.
[b] Between ages 20 and 40.

Table 13
Duration distribution of non-employment spells (%).

Duration (weeks):	Non-college[a]		College[b]	
	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

[a] Between ages 17 and 40.
[b] Between ages 20 and 40.

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 motivated by our discussion of the data in Section 2. 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 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 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

Table 14
Average accumulated hours of experience (in years).

Experience	Non-college[a]		College[b]	
	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

[a] Between ages 17 and 40.
[b] Between ages 20 and 40.

Table 15
Wage growth.

Wage growth	Non-college[a]				College[b]			
	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

[a] Ratio age 40/age 17.
[b] Ratio age 40/age 23.

Table 16
Contribution of children to the increase in the gender wage gap.

Economy	Non-college[a]		College[b]	
	Δ Wage gap	Contribution of children	Δ Wage gap	Contribution of children
Benchmark	0.25		0.22	
Only children	0.14	56%	0.10	45%
Only hours	0.11	56%	0.11	50%

[a] Between ages 17 and 40.
[b] Between ages 23 and 40.

in labor supply: Between ages 20 and 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 and 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 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 and age 40) and of 22 percentage points for college women (between age 23 and age 40). These statistics are 21 and 22 percentage points in the NLSY data. Hence, the

Table 17
Race experiment: wage growth of females.[a]

	Data	Model
Black non-college	1.77	1.75
All non-college	1.95	1.83
Ratio	0.91	0.94

[a] Between ages 17 and 40.

model accounts well for the increase in the gender wage gap. Our finding is consistent with that of Bertrand et al. (2010) 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. Moreover, Black et al. (2008) also conclude that human capital and labor supply factors can account for most of the gender wage gap in a study of U.S. college-educated women in the 1993 National Survey of College Graduates (NSCG).[18]

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 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 a 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%, 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.

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 10 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 11 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.

5.1. Discussion and relation to the literature

Our findings are consistent with the vast empirical literature that finds a substantial gender residual in wage regressions that measure human capital investments by past experience. To illustrate this point, we simulate non-college educated males and females in our model that are identical in terms of initial human capital and lifetime employment. Our simulated males and females only differ in lifetime labor supply because females work 10% less hours than males and because females expect to have children – with the associated negative impact on labor supply – even though ex-post no female is ever given an opportunity to have children. As a result, we simulate females that are identical to males when they enter the labor market and have an identical age-profile of employment over the life cycle. Since females in this experiment work more than 35 h a week, we follow the empirical literature in counting them as full-time employed. Hence, the data generated by this experiment features no gender differences in experience as measured by full-time employment. Nevertheless, we find a gender wage ratio of 0.875 at age 40: females earn on average a wage that is 12.5 percentage points lower relative to the average wage of males.[19] Using the simulated data, a standard wage regression of log wages on experience (measured as full-time employment) and a sex dummy as explanatory variables would attribute a negative wage effect to being a female

[18] In their non-parametric study they match individuals on age, highest degree, and major. When they consider women with "high labor market attachment", the estimated wage gap almost vanishes (it decreases from values above 0.30 to values in the range of 0.09 to 0.004, depending on the group of women considered).

[19] Note that the previous section we consider an experiment in which non-college women were not allowed to have children and we obtain a gender wage gap of 11% at age 40. In the current experiment, the gender wage gap is higher because women expect to have children, even though ex-post they do not have them. Expectations about children reduce human capital investments and lead to an increase in the gender wage gap of 1.5 percentage points.

worker and a lower return to (measured) experience by females relative to males. This experiment reveals that even females that are highly attached to the labor market face weaker incentives to invest in human capital than males that can generate sizeable gender wage gaps. Young females spend less effort in accumulating human capital than experience-equivalent males because they anticipate working less hours (even if employed full time). We conclude that, in the context of our model, standard measures of experience typically used in the empirical literature are not good measures of investment in human capital over the life cycle.

One concern is that our model may overstate the penalty to time off work due to childbirth. Because men's career interruptions are less frequent, and unrelated to childbirth, they may be more likely to signal a more extreme sort of heterogeneity. Since our calibration uses data from males to estimate the human capital technology, it is possible that our model exaggerates the negative impact of career interruptions on female wages. To evaluate this possibility, we use model simulated data to compare the wage of mothers and non-mothers. Following Waldfogel (1998) we compute the average wage ratio between women with children and women without children at a given age (the "family wage ratio"). We find that the family ratio in wages in our model for females 35–40 years of age is 0.85 which is quite similar to the 0.86 value in the NLSY data. Hence, our model does not appear to overstate the penalty to time off due to childbirth.

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. 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 not have 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. 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.

5.2. Race and the gender wage gap

While in the U.S. black women tend to have more children than white women, the gender wage gap is lower among blacks than among non-blacks. At first glance, this observation seems inconsistent with the predictions of our theory. Nonetheless, we now show that the theory is 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.[20] The main findings are:

- FACT 1: Black non-college women tend to have more children and to give birth at younger ages than the average non-college woman. The total fertility rate of non-college black women is 2.28 while it is 1.95 for non-college women (including all races). The timing of births also differs across black and the average non-college woman. About 30% of births occur before age 20 for black non-college women while such percentage is 18% for all non-college women.
- FACT 2: The labor supply of black non-college women is lower than the labor supply of the average non-college women. The accumulated experience at age 40 (in hours) is 13 years for black non-college women while it is 14.5 years for the average non-college woman.
- FACT 3: The gender wage gap at age 40 is lower among non-college black than among the average non-college population. While at age 17 the gender wage gap is small and does not vary across races, the gender wage gap at age 40 is 15 percentage points among black non-college while it is 23 percentage points among all non-college individuals.

The first two facts point that black women tend to have more children (at young ages) and to work less than the average non-college women, which is consistent with the view that children negatively affect the labor supply of females. Hence, our theory implies that black females should face lower incentives to accumulate human capital than the average non-college

[20] 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.

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 black individuals than for all non-college people. 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 and 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 among black individuals 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).[21] 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.[22] 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 20 and 21).

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

6. 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 detailed labor market histories of men and women from NLSY79 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 women are assumed to be identical to males in terms of the human capital technology, we assumed 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 NLSY 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 NLSY – with the oversample of blacks – 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 NLSY data.

[21] The question of why black males work few hours in the labor market is important but out of the scope of the current paper.
[22] The values of the recalibrated parameters are reported in Table 19 in the Appendix.

In future work, it would be important to investigate how differences in occupational choices matter for gender differences in hours of work and human capital accumulation. It will also be interesting to use an extended version of our framework to study how various factors affecting female labor supply over time impact on the gender wage gap. To deepen our understanding of the family and welfare, the model could be enhanced to incorporate a non-linear utility function on consumption together with savings and marriage decisions. These interesting but non-trivial extensions are left for future research.

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Appendix A

See Tables 18–21.

Table 18
Parameter values.

Non-college				College			
Parameter	Value	Parameter	Value	Parameter	Value	Parameter	Value
v_{17}	8.0	Δ	3%	v_{20}	35.10	Δ	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 19
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 20
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 21
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

Appendix B. Supplementary data

Supplementary data associated with this paper can be found in the online version at http://dx.doi.org/10.1016/j.euroecorev.2015.12.014.

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