

**Returns to Human Capital and Explaining the Recent
Decline of Married Women's Labor Supply: A Cohort
Approach**

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Dedication

To my family, who made all of this work possible, for their endless love and dedication.

Abstract

Essay One investigates the effects of changes in various determinants of labor supply on the dramatic changes from the older (the 1950s and earlier) cohorts to the younger (the 1960s and later) cohorts in life-cycle labor supply behavior, and ultimately provides a model-based quantitative explanation of the recent decline in the aggregate labor supply of married women. On the basis of the Current Population Survey data, it first documents that, while life-cycle labor supply profiles are non-overlapping and bell-shaped for the older cohorts, they are roughly flat for the younger cohorts, and from the mid-thirties of the life-cycle, the younger cohorts continue to supply less labor than the 1950s cohort does. Then in a life-cycle model of women's labor supply, the behavioral changes are explained by a combination of changes in various labor supply determinants, with the opportunity cost of childbearing (as represented by returns to work experience and the rate of human capital depreciation during a nonworking period) being the dominant contributor. In particular, relative to the older cohorts, the higher opportunity cost for the younger cohorts makes them supply more labor at the early stage of the life-cycle, delay childbearing to a later stage, and upon childbearing, stay out of the labor force, other things being constant. A calibration of the model demonstrates that the aggregate labor supply of married women would increase by 1.96 percentage points from 2000 to 2010 if there were no changes between the older and the younger cohorts in the labor supply determinants; however changing the determinants for the same period actually results in a reduction of aggregate labor supply by 1.36 percentage points. Of the 3.32 percentage points of the pseudo-reduction of married women's aggregate labor supply (difference between the hypothetical 1.96 percentage point increase and the actual 1.36 percentage point reduction), 67 percent is explained by the increased opportunity cost for the younger cohorts, and the rest is accounted for by a combination of changes in the tax code, business cycle conditions, and preferences, among others.

In Essay Two, on the basis of those respondents in the National Longitudinal Survey of Youth (NLSY) who change jobs with an intervening period of education reinvestment, the conventional assumption of linearity of log wages in years of schooling is strongly

rejected: a typical reinvestment for the 1980 through 1993 period is associated with a rise of about 3.5 percentage points in the estimated return to an additional year of schooling. The estimated marginal rate of return generally rises in the former education level, and reaches the maximum at 15 years of the former level (therefore 16 years of education after reinvestment), where an additional year of investment is associated with a rise in real hourly rate of pay by approximately 20 percent. Evidence also shows that, while the level of individuals' risk tolerance affects significantly the probability of returning to school, correcting for sample selectivity makes little difference in the results. Findings in the current paper survive a variety of robustness tests. The current cohort-based evidence is more helpful than existing evidence from cross-sectional data to individuals making schooling decisions.

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Chapter 1

Introduction

This dissertation emphasizes the importance of a cohort approach in dealing with some important issues in the education and the macro labor market. Essay One finds that the recent decline of married women's aggregate labor supply is explained by between-cohort changes in the life-cycle labor supply behaviors that are mostly generated by changes from the older to the younger cohorts in the opportunity cost of childbearing. Essay Two provides cohort-based evidence on nonlinearity in the return to human capital investment. After all, the current cohort-based evidence is more helpful than existing evidence from cross-sectional data to individuals making schooling decisions.

Essay One investigates the effects of changes in various determinants of labor supply on the dramatic changes from the older (the 1950s and earlier) cohorts to the younger (the 1960s and later) cohorts in life-cycle labor supply behavior, and ultimately provides a model-based quantitative explanation of the recent decline in the aggregate labor supply of married women. On the basis of the Current Population Survey data, it first documents that, while life-cycle labor supply profiles are non-overlapping and bell-shaped for the older cohorts, they are roughly flat for the younger cohorts, and from the mid-thirties of the life-cycle, the younger cohorts continue to supply less labor than the 1950s cohort does. Then in a life-cycle model of women's labor supply, the behavioral changes are explained by a combination of changes in various labor supply determinants, with the opportunity cost of childbearing (as represented by returns to work experience and the rate of human capital depreciation during a nonworking period) being the dominant contributor. In particular,

relative to the older cohorts, the higher opportunity cost for the younger cohorts makes them supply more labor at the early stage of the life-cycle, delay childbearing to a later stage, and upon childbearing, stay out of the labor force, other things being constant. A calibration of the model demonstrates that the aggregate labor supply of married women would increase by 1.96 percentage points from 2000 to 2010 if there were no changes between the older and the younger cohorts in the labor supply determinants; however changing the determinants for the same period actually results in a reduction of aggregate labor supply by 1.36 percentage points. Of the 3.32 percentage points of the pseudo-reduction of married women's aggregate labor supply (difference between the hypothetical 1.96 percentage point increase and the actual 1.36 percentage point reduction), 67 percent is explained by the increased opportunity cost for the younger cohorts, and the rest is accounted for by a combination of changes in the tax code, business cycle conditions, and preferences, among others.

Essay Two focuses on how returns change as individuals increase human capital investment over the course of their work career. On the basis of those respondents in the National Longitudinal Survey of Youth (NLSY) who change jobs with an intervening period of education reinvestment, the conventional assumption of linearity of log wages in years of schooling is strongly rejected: a typical reinvestment for the 1980 through 1993 period is associated with a rise of about 3.5 percentage points in the estimated return to an additional year of schooling. The estimated marginal rate of return generally rises in the former education level, and reaches the maximum at 15 years of the former level (therefore 16 years of education after reinvestment), where an additional year of investment is associated with a rise in real hourly rate of pay by approximately 20 percent. Evidence also shows that, while the level of individuals' risk tolerance affects significantly the probability of returning to school, correcting for sample selectivity makes little difference in the results. Findings in the current paper survive a variety of robustness tests. The current cohort-based evidence is more helpful than existing evidence from cross-sectional data to individuals making schooling decisions.

Chapter 2

Essay One: Explaining the Recent Decline of Married Women's Labor Supply: A Cohort Approach

2.1 Introduction

One of the most salient features of the U.S. labor market after World War II is the tremendous increase in the proportion of women, particularly married women, working outside the home. According to the Current Population Survey (CPS) data, per capita employment among prime age (25-59) married women prominently increased from 35.1 percent in 1962 to 71.4 percent in 2000. Since then, however, it has been falling, down to 67.6 percent in 2011, which is unprecedented after World War II.¹ While the continuous long-term

¹ Per capita employment is used as a measure of labor supply for the following reasons. First, the literature of structural modeling of married women's life-cycle labor supply behaviors (See, for example, Attanasio et al. (2008, p. 1518) and references therein), to which the current paper contributes, often assumes that individuals make choices between the paid-market and the non-market sector. Second, repeated reports have been made by existing studies that unemployment and out of the labor force are not distinct states (e.g., Clark and Summers (1982) and Gönül (1992)). Third, as explained by Polivka and Miller (1998) among others, the 1994 redesign of the Current Population Survey (CPS) tends to inflate the labor force size in the process of identifying the unemployed more correctly, which results in inconsistency in the labor force series before and after the redesign. Although adjustment factors have been developed to make the participation rate comparable over time, no factors allow the possibility that the effects of the redesign are different depending on, say, labor market conditions which are often treated as a labor supply

rise in married women's labor supply until the late 1990s has received much attention, the recent decline has not been sufficiently studied and needs to be under scrutiny. Which types of women are responsible for the recent episode? What factors explain the recent trend movements? Answers to these questions are helpful not only for projection of the future labor force size but also for effective macro labor market policies.

Some studies (e.g., Hotchkiss, 2006; Juhn and Potter, 2006; Mosisa and Hipple, 2006; Cohany and Sok, 2007; Macunovich, 2010) have tried to explain the recent decline of women's labor supply. For example, documenting that the labor force participation rate increased rapidly from the mid-1960s until the 1980s, but showed a slower rise in the 1990s and then a slight decline in the first half of the 2000s, Juhn and Potter (2006) use the micro-level data of the March Current Population Surveys to demonstrate that the trend movements of the overall participation rate are mainly attributed to those of the participation rate of married women, especially of married mothers. Most of these studies, however, are descriptive in nature, and they do not provide structural explanations of the recent trend change. A more thorough empirical analysis is conducted by Aaronson et al. (2006), who employ a regression-based cohort approach to quantitatively explain how much of the recent decline in the overall participation rate is explained by structural factors (e.g., gender, age, presence of children) and how much of it is explained by cyclical factors. They do not, however, investigate the contribution of each determinant to the reduction of the aggregate labor supply, but rather evaluate the contribution of a set of structural factors as a whole. In addition, all 'structural' factors are treated as exogenous in their analysis, which seems implausible considering that fertility choice, for example, is determined through the individual (or household) utility maximization problem. An interesting idea is introduced by Fogli and Veldkemp (2011) to explain the stagnation of women's participation after 2000. They explain the recent episode with a learning process of belief about the effect of mother's employment on the children's outcome. However they do not explain the recent decline quantitatively.

Another strand of research has investigated determinants of women's life-cycle labor supply on the cohort basis. Using data on relatively older cohorts (those who were born

determinant. The redesign, however, has little effect on the coverage of employment. Finally, that said, according to the official statistics, little difference is observed between the labor force participation rate and per capita employment in their trend movements.

in the 1950s or earlier), existing studies find important determinants of the life-cycle labor supply: returns to work experience, child care costs, gender wage gap, schooling, and husband's income. For example, Eckstein and Wolpin (1989) document the importance of changes in the return to work experience in explaining changes in the cohort labor supply behavior. Francesconi (2002) emphasizes that differential returns to part-time and full-time experience in the part-time and the full-time sector play an important role in the choice between the non-market and the paid-market sectors associated with fertility changes. Attanasio et al. (2008) find a combination of changes in child care costs and changes in the gender wage gap crucial in explaining between-cohort differences in women's life-cycle labor supply. Understanding cohort-specific labor supply behavior goes beyond knowing the importance of various determinants of women's labor supply. It provides a basis for a structural explanation of trend movements of aggregate labor supply of married women: how much of the recent decline in the aggregate labor supply of married women is attributed to changes in the life-cycle labor supply behavior of which cohort, and what factors determine the behavioral change, and by how much. In fact, as will be explained subsequently, there was a major structural change between the older cohorts and the younger cohorts (those who were born in the 1960s and 1970s) in the life-cycle labor supply behavior. None of the aforementioned studies, however, address the younger cohorts in their analysis nor do they attempt to explain the recent decline quantitatively.

The purpose of this paper is twofold: the study first investigates the causes of the dramatic changes from the older to the younger cohorts in the life cycle labor supply behavior, and then uses the results to quantitatively explain the recent decline in the aggregate labor supply of married women. Unlike existing studies (e.g., Eckstein and Wolpin, 1989; Francesconi, 2002; Attanasio et al., 2008) that analyze labor supply behaviors of the older cohorts, I focus on how labor supply behaviors have changed from the older to the younger cohorts. This is important for at least three reasons. First, analysis of the CPS sample documents that, while life-cycle labor supply profiles are non-overlapping and bell-shaped for the older cohorts, they are roughly flat for the younger cohorts, and from the mid-thirties of the life-cycle, the younger cohorts continue to supply less labor than the 1950s cohort does. I find that this change is even more dramatic than any other changes in the labor supply behavior among the older cohorts (which existing studies

have attempted to explain), and hence deserves greater attention to its underlying causes. Second, understanding the recent structural change in the cohort labor supply profile is also important for quantitatively explaining the recent decline of married women's labor supply, which is my ultimate goal. It is believed that the same determinants that explain the important changes from the older to the younger cohorts in the labor supply behavior also explain the recent decline in the aggregate labor supply of married women. This is so because, at a point in time, the total labor supply is an aggregation of the amounts of labor supplied by all cohorts and, focusing on the mid-thirties and later stages of the life-cycle, each successive older cohort supplied more labor than the previous one up to the 1950s cohort, after which the younger cohorts started to supply less labor than the 1950s cohort. Third, I believe that the recent changes in the cohort-specific life-cycle labor supply behavior are closely connected to the well-known phenomenon of delayed childbearing. For example, Mathews and Hamilton (2009) report that, while the average age at first childbirth increased between 1970 and 2006, the increases were more dramatic during the first two decades (1970 to 1990). These two decades are in fact the periods of childbearing for the 1950s and 1960s cohorts. Consequently, what caused the recent changes in the cohort labor supply behavior is likely to have caused the concurrent changes in married women's decisions on childbearing. My model is developed to identify the determinants that simultaneously explain changes in cohort labor supply behaviors and in the timing of childbearing. As for the purpose of a quantitative explanation of the recent downward trend, unlike Aaronson et al. (2006) I present a model-based explanation of how changes in each structural factor contribute to changes in the aggregate labor supply of married women as well as changes in the life-cycle labor supply of each cohort, and treat fertility choice, among others, as an endogenous variable in the life-time utility maximization framework. This paper contributes to both the literature on structural modeling of married women's life-cycle labor supply and the literature on trends in women's labor supply.

The major findings are as follows. First, this paper documents important changes from the older to the younger cohorts in labor supply behavior, as previously stated. Second, in a life-cycle model of women's labor supply, the behavioral changes are explained by a combination of changes in the opportunity cost of childbearing (as represented by returns to full-time and part-time work experience and the speed of human capital depreciation

during nonworking periods), children-related tax credits, business cycle conditions, and preferences, with the opportunity cost being the dominant contributor. In particular, the increase in the opportunity cost has made the younger cohorts delay childbearing and stay out of the labor force in subsequent stages of the life-cycle. To be specific, compared with the older cohort, younger ones experience higher marginal returns to full-time work experience, lower returns to part-time experience, and higher rates of human capital depreciation during nonworking periods, all of which induce younger cohorts to pursue full-time work in the early stage of the life-cycle and delay childbirth. The relatively low returns to part-time experience tend to make the younger cohorts withdraw from the paid-market when they are separated from the full-time sector. Furthermore, due to the higher human capital depreciation rate for the younger cohorts, the probability of returning to the paid-market from the non-market sector is lower for the younger cohorts than the older ones. Additional analysis reveals that, in contrast to existing studies (Ribar, 1992; Martinez and Iza, 2004; Attanasio et al., 2008), changes in child care costs no longer explain between-cohort changes in the labor supply behavior, mainly because there is little change in child care costs between the older (especially the 1950s cohort) and the younger cohorts. A calibration of the model demonstrates that the aggregate labor supply of married women would increase by 1.96 percentage points from 2000 to 2010 if there were no changes between the older and the younger cohorts in the labor supply determinants; however changing the determinants for the same period actually results in a reduction of aggregate labor supply of married women by 1.36 percentage points. Of the 3.32 percentage points of the pseudo-reduction of aggregate labor supply (difference between the hypothetical 1.96 percentage point increase and the actual 1.36 percentage point reduction), 67 percent is explained by the increased opportunity cost of childbearing for the younger cohorts, and the rest is accounted for by a combination of changes in the tax code, business cycle conditions, and preferences, among others.

The rest of the paper is organized as follows. On the basis of the Current Population Survey data, Section 2.2 explains how cohort-specific as well as aggregate labor supply of married women has changed over time. Section 2.3 presents the model. Section 2.4 deals with estimation of cohort-specific wage functions, whose results play a crucial role in explaining between-cohort changes in the labor supply function. Section 2.5 describes the

model calibration. Section 2.6 investigates the effects of changes in various determinants of labor supply on between-cohort changes in the life-cycle labor supply behavior. Using the results from Section 2.6, Section 2.7 provides a comprehensive quantitative explanation of the recent decline in the aggregate labor supply of married women. Section 2.8 concludes.

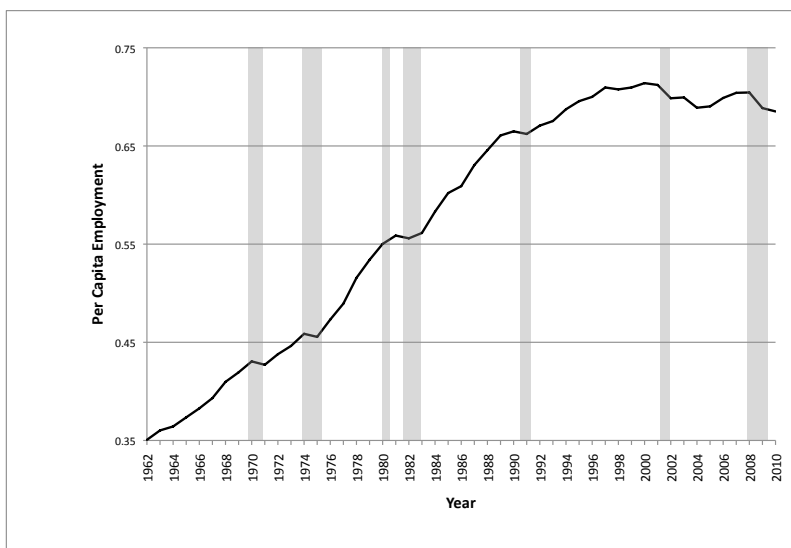
2.2 The Facts

This section provides some basic facts about trend movements in the overall and cohort-specific labor supply of prime age (25-59) married women. While I follow existing studies (e.g., Juhn and Potter, 2006; Hotchkiss, 2006; Macunovich, 2010; Moffitt, 2012) to use the March CPS to document these facts, official statistics, not reported for brevity, show that trend movements of per capita employment are virtually identical between the March CPS and the annual average, which is true for the group of prime age married women as well as all women.

2.2.1 Trends in Per Capita Employment

Figure 2.1 displays how per capita employment has evolved over the 1962 to 2010 period. Per capita employment of all prime age married women increased almost continuously from 35.1 percent in 1962 to 71.4 percent in 2000, with most of the rise occurring before 1990, pausing only briefly in recessions, signified by the shaded regions. Since 2000, however, it declined to 68.5 percent in 2010. One thing to keep in mind is that even for the 2006 to 2008 period, where per capita employment reached the local peak between the minor recession in the early 2000s and the current Great Recession, its level (about 70 percent) is still lower than the historical peak (71.4 percent) in 2000, implying that the recent labor force withdrawal reflects a reversal of a long-term trend.

Table 2.1 compares per capita employment across various demographic and economic groups. These groups are commonly considered when analyzing labor supply behaviors of married women. Overall, little heterogeneity is observed across groups in the pattern of trend movements of per capita employment, except for age groups. For example, focusing on the recent decline between 2000 and 2010, estimates in Panel A show that per capita employment decreased for both the high school group (those with a high school degree or



Source: The author's calculation using the March Current Population Survey micro data, 1962-2010.

Figure 2.1: Per Capita Employment of Prime Age (25-59) Married Women

less) and the college group (those with some college or more). Precisely, it went down by 4.9 and 3.2 percentage points for the high school group and the college group, respectively. The greater labor force withdrawal among less educated married women seems at odds with the phenomenon of the Opt-Out Revolution, first sensationalized by Lisa Belkin in a 2003 *New York Times* article, referring to the fact that highly educated women, relative to their less educated counterparts, are exiting the labor force to take care of their families at higher rates today than in earlier time periods. While studies by Thornton and Young-DeMarco (2001), Mosisa and Hipple (2006), Hoffman (2009), and Antecol (2010) support the 'Opt-Out Revolution', results from Boushey (2005), Goldin (2006)², and Percheski (2008) are more consistent with the current observation. Similar reductions are observed from Panels *B* and *C* in Table 2.1, where per capita employment is displayed conditional on the presence of children and for assortative patterns of marriage which depend on the wife's and the husband's education levels.

When it comes to age groups, however, per capita employment shows somewhat different trend movements across different groups. In particular, from 2000 to 2010, the 55-59

² Goldin's stance is conservative, mentioning that the life-cycle labor supply of recent cohorts cannot be judged with the short length of the longitudinal information.

group shows a rapid increase in per capita employment (5.2 percentage points), and the 50-54 group reveals little change, when all the other younger age groups experience substantial reductions (4 to 7 percentage points). Different cohort effects are initial suspects of the heterogeneity. In fact, the substantial increase in per capita employment among the 55-59 age group is observed by comparing per capita employment of the early 1940s cohort as of 2000 with that of the early 1950s cohort as of 2010. In contrast, the large reduction of per capita employment among, say, the forties (40-49 age group) is observed from the comparison of employment of the 1950s cohort as of 2000 and that of the 1960s as of 2010. Subsequent sections will be devoted to investigation of whether and when there was a ‘structural’ break between different cohorts in the life-cycle labor supply behavior and what factors can explain the behavioral change.³

2.2.2 Between-Cohort Changes in the Life-Cycle Labor Supply

Now I turn my attention to cohort-specific life-cycle labor supply behaviors, which are expected to play a central role in explaining the recent decline in married women’s labor supply. Figure 2.2 plots cohort-specific per capita employment against different stages of the life-cycle. For brevity of illustration, I select the three most recent cohorts from the group of older cohorts: the 1930s (the grey dashed line), the 1940s (the grey dotted line)

³ Surely, the current discussion neglects the effects of changes in the population share of each group on the decline of aggregate labor supply of married women. As can be seen from APPENDIX A.2, however, changing population shares are not likely to explain the recent labor force withdrawal, no matter what economic/demographic groups are adopted in the analysis. For example, focusing on the change from 2000 to 2010, the population share has increased for the college group whose per capita employment is typically higher than that of the high school group. For the same period, the population share also increased among the group of married women who have no child. As shown in Table 2.1, per capita employment has been higher for this group than those married women with children. Using figures in Table 2.1 and APPENDIX A.2, I formally decompose the reduction in per capita employment between 2000 and 2010 into two components: one is the portion of the reduction associated with changes in the population share of each subgroup, and the other is the portion that is generated by changes in group-specific per capita employment. Analysis confirms that, no matter what economic/demographic groups are adopted, changes in the population share do not play a role in explaining the recent decline in aggregate labor supply of married women. For example, when the population is divided into two education groups as in Panel *A*, changes in the population share for the 2000 to 2010 period negatively explain 35 percent of the reduction in aggregate labor supply. When the population of married women is divided into two groups depending on presence of children (Panel *B*), the estimated share effect is close to zero. Estimated share effects are also negative when the other two group classifications are followed. These observations suggest that answers to the current research questions can be sought by exploring changes in the labor supply behavior across different cohorts.

Table 2.1: Per Capita Employment of Prime Age (25-29) Married Women by Various Groups

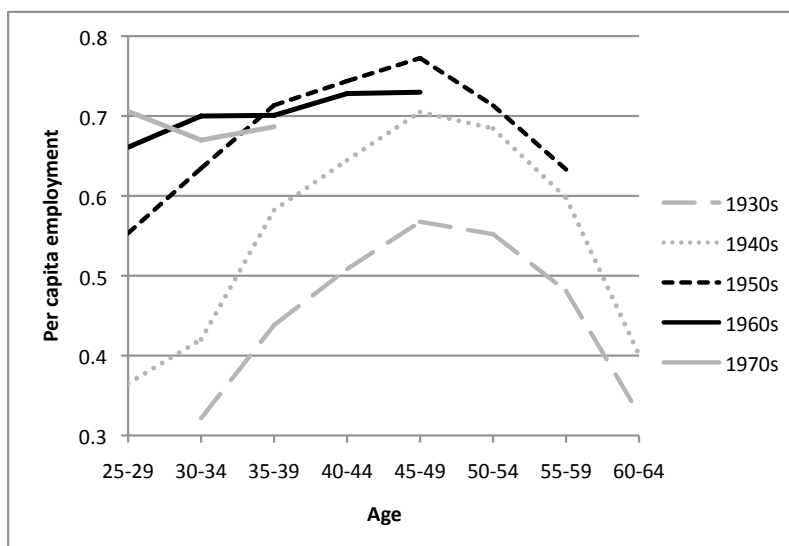
	Year						
	1980	1985	1990	1995	2000	2005	2010
Women (25-59)	55.0	60.2	66.5	69.6	71.4	69.3	68.5
<i>A. Education</i>							
High school or less	51.2	55.0	60.8	62.5	64.5	60.2	59.6
Some college or more	63.2	69.1	74.3	75.7	76.7	74.7	73.4
<i>B. Presence of children</i>							
With no children	58.4	62.8	68.6	71.1	73.5	71.4	71.2
With children	53.0	58.5	65.0	68.5	69.8	67.1	66.3
<i>C. Types of marriage</i> ^a							
Wife(<i>H</i>), Husband(<i>H</i>)	50.2	54.2	59.4	60.9	63.6	59.1	58.2
Wife(<i>H</i>), Husband(<i>C</i>)	52.0	56.5	63.5	64.8	64.9	61.8	61.4
Wife(<i>C</i>), Husband(<i>H</i>)	65.5	69.4	78.0	76.8	79.6	76.1	74.6
Wife(<i>C</i>), Husband(<i>C</i>)	62.1	68.8	73.0	75.5	75.5	74.0	73.0
<i>D. Age</i>							
25-29	55.8	61.6	66.0	66.6	69.0	62.6	63.4
30-34	56.3	61.7	66.7	69.5	69.5	66.5	65.1
35-39	58.2	65.1	70.3	72.6	72.6	68.9	68.5
40-44	68.5	64.5	72.3	74.0	76.5	73.6	69.7
45-49	57.7	62.7	70.5	74.1	76.9	74.1	73.2
50-54	50.3	56.2	62.1	68.4	72.9	71.9	71.6
55-59	42.7	44.3	49.9	53.5	59.8	61.4	65.0

Source: The author's calculation using the March Current Population Survey micro data, 1980-2010.

^a *H* and *C* represent 'High school or less' and 'Some college or more', respectively.

and the 1950s (the dark dashed line). Among the younger cohorts, the 1960s cohort is represented by the dark solid line, and the 1970s by the grey solid line. Evidently, there have been important changes in the life-cycle labor supply behavior from the older cohorts to the younger cohorts: while life-cycle labor supply functions are non-overlapping and bell-shaped for all the older cohorts, they are roughly flat for the younger cohorts. In addition, focusing on the mid-thirties and later stages of the life-cycle, each successive older cohort supplied more labor than the previous one up to the 1950s cohort, after which the younger cohorts start to supply less labor than the immediate predecessor. I find that this change is even more dramatic than any other changes in the labor supply behavior among older cohorts. This structural change will also play a crucial role in quantitatively explaining

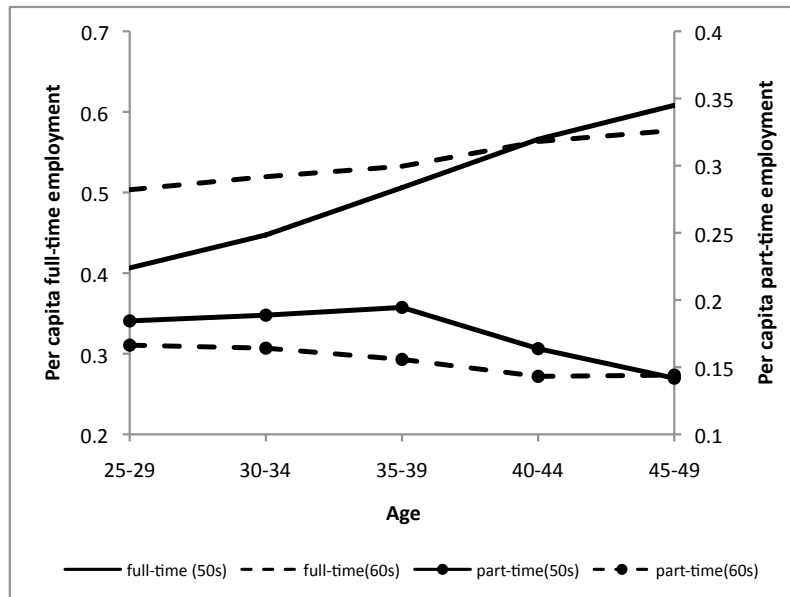
the recent decline in married women's labor supply, for reasons stated previously.



Source: The author's calculation using the March Current Population Survey micro data, 1965-2010.

Figure 2.2: Per Capita Employment over the Life-Cycle by Cohort

For a more detailed investigation of how the life-cycle labor supply behavior has changed from the older to the younger cohorts, Figure 2.3 further divides per capita employment between per capita full-time employment and per capita part-time employment. In classifying the extent of the labor market involvement into three states, full-time work, part-time work, and nonwork, I follow existing studies (Nakamura and Nakamura, 1983; Corcoran et al., 1983; Francesconi, 2002) that define non-workers as those who work less than 500 annual hours, part-timers by those who work between 500 and 1,500 hours, and full-timers by those who supply more than 1,500 hours. Information on annual hours is obtained from the March Supplement to the CPS, where individuals report annual work hours for the previous year. For brevity, I contrast per capita employment only between the 1950s and the 1960s cohorts and only for a comparable period of the life-cycle. The solid line represents per capita full-time employment for the 1950s cohort, the solid line connecting circular data points represents per capita part-time employment for the 1950s cohort, the dashed line represents per capita full-time employment for the 1960s cohort, and the dashed line connecting circular data points stands for per capita part-time employment for the 1960s



Source: The author's calculation using the March Current Population Survey micro data, 1975-2010.

Figure 2.3: Per Capita Employment by Sector and by Cohort

cohort.

The most striking pattern observed in Figure 2.3 is that, while per capita full-time employment is higher for the younger cohort than the older cohort in the early stage of the life-cycle, it increases at a faster rate for the older cohort than for the younger cohort. As a result, from the early forties and on, per capita full-time employment is higher for the older cohort than for the younger cohort. As for employment in the part-time sector, per capita part-time employment for the younger cohort is lower than that for the older cohort from the early twenties to the early forties of the life-cycle. While the former generally decreases over the course of the life-cycle, the latter first increases slightly until the late thirties and then decreases at a faster rate relative to the former. Put together, the greater labor supply among the younger cohorts relative to the older at the early stage of the life-cycle comes from the younger cohorts' greater involvement in the full-time sector at the early stage of the life-cycle. Together with the slower employment growth in the full-time sector for the younger than for the older cohort, it is mainly responsible for the dramatic changes from the older to younger cohorts in the life-cycle labor supply behavior, as previously stated.

Table 2.2: Sectoral Distribution of Married Women Before/After Childbirth

Status	Time distance from childbirth				
	$t - 1$	$t + 2$	$t + 7$	$t + 12$	$t + 17$
1950s cohort					
Nonwork	0.192	0.453	0.386	0.289	0.226
Part-time	0.167	0.223	0.212	0.210	0.181
Full-time	0.641	0.324	0.402	0.501	0.593
1960s cohort					
Nonwork	0.147	0.383	0.375	0.342	
Part-time	0.132	0.207	0.183	0.180	
Full-time	0.720	0.410	0.442	0.478	

Source: The author's calculation using the Panel Study of Income Dynamics, 1976-2009.

Those who have one or two children are included in the sample.

t represents the birth year of the first child.

Bearing the above observed patterns in mind, Table 2.2 examines how childbirth is related to dynamics of sectoral choice of married women. For that purpose, I use the longitudinal information contained in the Panel Study of Income Dynamics (PSID). The PSID administered the survey every year from 1968 to 1997, and every other year since then. To meet the age requirement of the 1950s cohort, I use the surveys from 1976 through 2009. To be included in the sample, respondents should have one or two children by age 40. The numbers in the table represent the sectoral percent distribution of married women. Sampling weights are used to derive the estimates. In the table, year t represents the birth year of the first child. Estimates show that the proportion of full-time employment is much higher for the younger than the older cohort before childbirth. While the proportion of full-time employment drops substantially right after childbirth for both cohorts, recovery from the drop is much slower for the younger than the older cohort. Due to the faster rise in the full-time employment of the older cohort relative to the younger, the size of the full-time sector of the older cohort catches up to that of the younger in a decade or so after first childbirth. The slower recovery of the full-time sector employment for the younger cohort is associated with the younger cohort's slower exodus from the non-market sector relative to the older cohort. Consequently, in a decade after first childbirth, the size of the non-market sector of the younger cohort begins to outgrow that of the older cohort.

Lastly, the proportion of part-timers is lower for the younger than the older cohorts.

Regarding the timing of first birth, it is well-known that the average age at first childbirth has increased significantly for the last half century. Using data from the Birth Data File, National Vital Statistics System, Mathews and Hamilton (2009) report that the average age of mother at first childbirth increased from 21.4 in 1970 to 25.0 in 2006, with more dramatic increases during the first two decades (1970 to 1990). As previously stated, these two decades are in fact the periods of childbearing for the 1950s and the 1960s cohort. Their additional analysis shows that the dramatic increase in women having their first birth at the age of 35 and over has played the greatest role in the increased average age at first childbirth: in 1970, 1 out of 100 first births was to women aged 35 years and over, compared with 1 out of 12 in 2006. Using the June Supplement to the CPS, I also find that the share of old mothers (those who have the first child at ages 30 to 39) among the total married women is 21.9%, 28.2% and 29.1% for the 1950s, the 1960s, and the 1970s cohort, respectively. Again, the increase in the share of old mothers is particularly large between the 1950s and the 1960s cohorts. These observations make me believe that the dramatic changes from the 1950s cohort to the 1960s in the life-cycle labor supply behavior are closely connected to the dramatic increase from 1970 to 1990 in the average age at first childbirth, and what caused the recent changes in the cohort labor supply behavior is likely to have caused the concurrent changes in married women's decisions on childbearing. Subsequent sections will explain how my model identifies the determinants whose changes simultaneously explain changes in cohort labor supply behaviors and the phenomenon of delayed childbearing.

2.3 The Model Economy

2.3.1 Economic Environment

The economy is populated by households that consist of a married couple who remain married, with or without children. Both a husband and a wife live T periods. Let $a \in \{a_1, a_2, \dots, a_T\}$ denote a period (or 'age') of the life-cycle, which consists of five years of actual ages. Adults in the household start economic activity at age a_1 , retire at a_R . After retirement, the household receives a pension of 90 percent of the husband's earnings

until a_T . In each period, the household makes decisions on the wife's labor supply and fertility, along with household consumption and savings.⁴ To be specific, in each period, the household chooses the wife's employment 'sector' among full-time, part-time, and nonwork. The husband always works in the full-time sector. When the wife works, she experiences different rates of wage growth depending on endogenously accumulated sector-specific work experience, while she loses human capital in a nonlinear fashion during a nonworking period. The household also chooses the number of new children in each period until the wife gets to a_I , after which she is considered to be infertile. Newborn children are attached to the household until they reach a certain age, after which they leave the household. The wife is the one who takes care of children. The children impose costs when the wife works. The household pays three different types of taxes: income tax, capital tax, and payroll tax.

Child care costs

When the wife works, the household pays for child care costs that depend on the number of children, ages of children, and the wife's working hours. Since child care costs increase with wife's working hours (n^w) (Ribar, 1992, 1995), the total amount of child care costs is mn^w , where m is per hour child care costs.

Wages and human capital

Both the husband's and the wife's wages are stochastic with permanent shocks (Attanasio et al., 2008). Since the husband always works, his human capital accumulation process depends on age. The wife's human capital accumulation process, however, depends on endogenously accumulated sector-specific (full-time and part-time) work experience (Corcoran et al., 1983; Blank, 1989b; Blossfeld and Hakim, 1997; Francesconi, 2002), and her wages depreciate nonlinearly during a nonworking period. The husband's and the wife's wages are also affected by business cycle conditions, as represented by unemployment rates.

⁴ Allowing the saving choice is important because it makes the model more flexible in regards to consumption smoothing over the life-cycle: without the saving choice, the only way to substitute consumption intertemporally is to change labor supply, exaggerating the role of labor supply in consumption smoothing over the life-cycle (French, 2005; van der Klaauw and Wolpin, 2005; Attanasio et al., 2008).

Taxes

A typical household pays income tax, payroll tax, and capital tax and their rates are denoted by τ_I , τ_p , and τ_k , respectively. Let A , r , n^h , w^h , and w^w denote asset, interest rate, husband's working hours, husband's wages, and wife's wages, respectively. Then the total household income is given by $rA + w^h n^h + w^w n^w$, where capital income is represented by rA , and labor income is denoted by $w^g n^g$ for $g = \{h, w\}$, with h and w representing husband and wife, respectively. The income tax rate (τ_I) depends on the total household income, the number of children, and the calendar year reflecting changes in the tax code, with which the total income tax liability (T_I) is calculated. I assume that the government does not levy income taxes on annuities after retirement (Gunner et al., 2012a,b). The other types of tax rates (τ_k on the capital income and τ_p on the labor income) are flat but vary depending on the calendar year.

Preferences

Preferences that a typical household faces are given by

$$U(c, n^w, k, m) = u(c, n^w) + x(k, n^w, m)\mathbb{I}_{(k>0)} \quad (2.1)$$

where c represents the household size-adjusted consumption⁵, k is the number of children, and $\mathbb{I}(\cdot)$ denotes the indicator function. I borrow utility function (2.1) from Caucutt et al. (2002), but generalize it by using the CES (Constant Elasticity of Substitution) functional form instead of Cobb-Douglas for the child care production function, $x(\cdot)$. To be specific, $u(\cdot)$ and $x(\cdot)$ are represented by

$$u(c, n^w) = \frac{c^{1-\gamma}}{1-\gamma} + \eta n^w \quad (2.2)$$

$$x(k, n^w, m) = \delta \frac{k^{1-\theta} [(g(\frac{1-n^w}{k})^\phi + (1-g)(\frac{mn^w}{k})^\phi)^{1/\phi}]^{1-\lambda}}{1-\theta} \quad (2.3)$$

⁵ For the household size-adjusted consumption, I use the OECD-modified scale that assigns a value of 1 to the husband, 0.5 to the wife, and 0.3 to each child.

where $u(\cdot)$ is composed of the utility of per capita consumption and the disutility of work. $x(\cdot)$ depends on the number of children (k), the wife's child care hours ($1 - n^w$) and the market goods for child care (m). γ is a coefficient of relative risk aversion of consumption, η is the weight on disutility of work, δ is the weight on child care production, θ is a coefficient of relative risk aversion of the number of children (quantity of children), λ is a coefficient of relative risk aversion of the quality of children, ϕ concerns the elasticity of substitution between mother's time ($\frac{1-n^w}{k}$) and market goods ($\frac{mn^w}{k}$), and g is the relative share of mother's child care time to child care market goods.

2.3.2 The Decision Problem of a Household

In each period, the household decides how much to consume and save, how many new children to have, and which employment sector the wife gets involved in. Precisely, the household faces eighteen mutually exclusive alternatives depending on the fertility choice (represented by the number of new children, 0 through 5) and the decision on the wife's employment sector (among full-time, part-time, and nonwork), which are denoted by $j \in \{1, 2, \dots, 18\}$: $j = 1$ if 0 children and the full-time sector; $j = 2$ if 0 children and the part-time sector; $j = 3$ if 0 children and nonwork; $j = 4$ if 1 child and the full-time sector; $j = 5$ if 1 child and the part-time sector; and $j = 6$ if 1 child and nonwork; all the way up to $j = 16$ if 5 children and the full-time sector; $j = 17$ if 5 children and the part-time sector; and $j = 18$ if 5 children and nonwork. Once the household chooses the wife's employment sector, the wife's working hours are pinned down as 0 hours for nonwork, 1,000 hours for part-time work and 2,100 hours for full-time work.⁶ As hours in the full-time sector are normalized as 1, part-timers are to work 0.48 hours.

Let $\Omega = \{A, a, \nu^h, \nu^w, k_-^y, k_-^m, k_-^o, X_-^f, X_-^p, X_-^n, t\}$ be a set of state variables for the household problem, where ν^h and ν^w represent the permanent shock to the husband's and the wife's wages respectively; k_-^y , k_-^m , and k_-^o represent the number of children in the prior period, with k_-^y standing for the number of children between ages 0 to 4, k_-^m for ages 5 to 9, and k_-^o for ages 10 to 14; X_-^f , X_-^p , and X_-^n denote cumulative full-time, part-time, and

⁶ On the basis of the March CPS from 1980 through 2010, I calculated these figures by first averaging annual hours of married women in each of year-by-sector cells and by averaging the sector-specific annual hours over time. While averaged, these figures remain relatively stable over time.

nonwork experience, respectively, in the prior period; and t is the calendar year.

Each household maximizes expected utility, and its decision problem is given by

$$V(\Omega) = \begin{cases} \max\{V^1(\Omega), V^2(\Omega), \dots, V^{18}(\Omega)\} & \text{if } 1 < a \leq a_I \\ \max\{V^1(\Omega), V^2(\Omega), V^3(\Omega)\} & \text{if } a_I < a < a_R \\ V^3(\Omega) & \text{if } a_R \leq a \leq a_T \end{cases} \quad (2.4)$$

and the value function of each case is defined by

$$V^j(\Omega) = \begin{cases} \max_{c, A'} \{U^j(c, n^w, k, m) + \beta EV(\Omega'|\Omega, j)\} & \text{if } a < a_T \\ \max_c U^j(c) & \text{if } a = a_T \end{cases} \quad (2.5)$$

subject to

$$\begin{aligned} C + A' &= A(1 + r(1 - \tau_k)) + w^h(1 - \tau_p) + w^w(1 - \tau_p)n^w - mn^w - T_I \\ 0 &\leq n^w \leq 1, \quad C \geq 0, \\ A &= 0 \text{ (if } a = 1), \quad A' \geq 0 \text{ (with strict equality if } a = a_T) \end{aligned}$$

where β represents the discount factor.

Since the household can have up to 5 new children in each period, $k^y = \{0, 1, 2, \dots, 5\}$, $k^m = \{0, 1, 2, \dots, 5\}$, and $k^o = \{0, 1, 2, \dots, 5\}$. The total number of children (k) is the sum of the number of children over the three age groups, that is, $k = k^y + k^m + k^o$. The number of children of each age group evolves as follows:

$$\begin{aligned} k^y &= k_-^y + d^e - d^l \\ k^m &= k_-^m + d^e - d^l \\ k^o &= k_-^o + d^e - d^l \end{aligned} \quad (2.6)$$

where d^e and d^l represent the number of children entering and leaving the children's age group, respectively, such that $d^e = \{0, 1, \dots, 5\}$ and $d^l = \{0, 1, \dots, 5\}$.

Sector-specific work experiences evolve according to

$$\begin{aligned} X^f &= X_-^f + 5F \\ X^p &= X_-^p + 5P \\ X^n &= X_-^n + 5N \end{aligned} \tag{2.7}$$

where F , P , N are dichotomous variables equal to 1 if the wife works in the full-time sector, the part-time sector, and the non-market sector, respectively.

The model is solved numerically. A numerical solution requires calculating $EV(\Omega'|\Omega, j)$ in Equation (2.5) by a typical backward recursion for all j and elements of Ω . In solving the model, a potential nonconcavity problem arises because of the nature of the discrete choice associated with changes in the wife's employment sector and the new number of children in the future period. With enough uncertainty, however, changes in the wife's employment sector in the future period will be smoothed out, leaving the expected value function concave (Attanasio et al., 2008). The Detailed numerical method is described in APPENDIX A.3.

2.4 Wages and Human Capital

Existing studies stress the importance of returns to work experience as a determinant of women's labor supply. Using a structural dynamic model, a seminal work by Eckstein and Wolpin (1989) documents a large positive effect of work experience on wages, which leads to a persistent state dependence on work experience. O'Neill and Polachek (1993) and Blau and Kahn (1997) show that returns to work experience increased for women by a large amount during the 1970s and the 1980s, suggesting an enhanced incentive to accumulate work experience. Olivetti (2006) documents that the significant increase between the 1970s

and the 1990s in working hours for married women with children was in large part attributed to an increase in returns to experience that endogenously increased working hours further. Similarly, Caucutt et al. (2002) show that an increase in returns to experience for women causes a delay in the timing of childbirth.

Some studies (Corcoran et al., 1983; Francesconi, 2002) further distinguish the part-time sector from the full-time sector in women’s labor force decisions. In particular, Francesconi (2002) emphasizes that not only are returns to full-time experience generally different from returns to part-time experience, but also returns to full-time (or part-time) experience vary depending on the sector (full-time or part-time) individuals are engaged in, suggesting that different sectors have different degrees of transferability of human capital. These factors require division of sectors when analyzing women’s choice problems associated with childbirth. Indeed, Blank (1989b) and Blossfeld and Hakim (1997) show that part-time work provides a bridge or an occasional alternative to full-time employment during the child bearing/rearing period. Bearing all of these messages in mind, this section is devoted to estimation of the wage function, which plays the central role in explaining cross-cohort changes in the labor supply behavior.

2.4.1 Estimation Methods

In estimating the husband’s wage function, I borrow the specification adopted by Olivetti (2006) and Attanasio et al. (2008), among others, and augment it by including the unemployment rate as an additional regressor.

$$\ln w_{i,t}^h = \alpha_1 + \alpha_2 a_{i,t} + \alpha_3 a_{i,t}^2 + \alpha_4 u_t + \omega_{i,t} \quad (2.8)$$

where $w_{i,t}^h$ represents the real hourly earnings of husband i in year t , $a_{i,t}$ his age, u_t the unemployment rate, and $\omega_{i,t}$ is the error term. As in most existing studies, husbands are assumed to be employed in the full-time sector all the time, requiring neither division of sectors nor correcting for sample selectivity.

In estimating the wife’s wage function, I augment Francesconi (2002)’s specification by adding the nonworking period and the unemployment rate as additional regressors.

$$\begin{aligned}
\ln w_{i,t}^w &= \beta_0 + \beta_1 X_{i,t-1}^f + \beta_2 (X_{i,t-1}^f)^2 + \beta_3 X_{i,t-1}^p + \beta_4 (X_{i,t-1}^p)^2 + \beta_5 X_{i,t-1}^n + \beta_6 (X_{i,t-1}^n)^2 \\
&\quad + \beta_7 P_{i,t} X_{i,t-1}^f + \beta_8 P_{i,t} (X_{i,t-1}^f)^2 + \beta_9 P_{i,t} X_{i,t-1}^p + \beta_{10} P_{i,t} (X_{i,t-1}^p)^2 + \beta_{11} P_{i,t} X_{i,t-1}^n \\
&\quad + \beta_{12} P_{i,t} (X_{i,t-1}^n)^2 + \beta_{13} u_t + \epsilon_{i,t}
\end{aligned} \tag{2.9}$$

where $X_{i,t-1}^f$, $X_{i,t-1}^p$, and $X_{i,t-1}^n$ represent cumulative duration of full-time, part-time, and nonworking experience, respectively, for individual i as of year $t - 1$; $P_{i,t}$ is a dummy variable which equals one if the wife works in the part-time sector in year t , and zero otherwise; u_t is the unemployment rate; and $\epsilon_{i,t}$ is the error term.

Some econometrics issues are worth noting in estimating Equation (2.9). First, wages are observed only when wives are employed. If the effects of the wage determinants (for example, returns to full-time experience) for those who are not employed differ systematically from those for employed wives, then Ordinary Squares Estimation (OLS) of Equation (2.9) leads to biased and inconsistent estimates of the regression coefficients. To correct for the sample selectivity, I employ the conventional two-step estimation method suggested by Heckman (1979). With the selection term included as an additional regressor in the second-step estimation, identification of coefficients requires at least one variable excluded from the wage equation, but included in the selection term. Following existing studies in the literature (e.g., Olivetti, 2006), I use the number of children and husband's income as those excluded variables.⁷ Second, the error term in the wife's (and also in the husband's) equation is likely to be cross-sectionally correlated because different individuals' error terms share common year effects. Neglecting this would bias the estimated standard error of the estimated business cycle effect downward. To obtain appropriate standard error estimates, I conduct White's standard error estimation that is robust with respect to the within-year clustering.

Estimation of Equation (2.9) requires longitudinal information on individuals' labor market experience collected for a sufficiently extended time period. This is so because the equation is estimated for different cohorts separately, and even for each cohort, I need to allow enough variation across individuals and over time in the measured cumulative

⁷ A Sargan test barely accepts the null hypothesis of non-correlation of the excluded variables and the error term in the wage equation.

duration of each individual’s full-time, part-time, and non-market experience since the entry into the labor market. The PSID is the most suitable for this purpose, because it covers a wide range of different cohorts, and has been tracking individuals’ labor market experience over four decades. To ensure enough degrees of freedom, I use both the Survey Research Center (SRC) and the Survey of Economic Opportunity (SEO) components of the PSID sample, with appropriate sample weights. To compare different cohorts (mostly the 1950s and the 1960s cohorts) for the same period of the life-cycle, I restrict the sample to individuals aged 25-49, which limits my sample period of wage observations from 1980 to 2009.

In each survey, respondents report annual earnings and annual hours for the previous year. The dependent variable is measured by the ratio of annual earnings deflated by the Consumer Price Index (CPI) to annual hours. For the purpose of measuring cumulative duration variables, I first define full-time, part-time, and nonworking experience on an annual basis, following the criteria mentioned in the discussion of Figure 2.3. Then, starting from 1980, average hourly earnings of a wife in year t are matched with the sum of the full-time years, sum of the part-time years, and sum of the nonworking years she experienced since her entry into the labor market until year $t - 1$, along with the contemporaneous unemployment rate.

2.4.2 Results

Table 2.3 reports estimation results of the husband’s wage equation. As the estimated coefficients are similar across cohorts, I pool the sample across different cohorts and estimate a ‘representative’ wage function for all cohorts. These estimates will be used for subsequent discussions of the model calibration.

Table 2.4 reports the main results for wives. Results are obtained by applying OLS to Equation (2.9) with the sample selectivity accounted for. For brevity, only estimated coefficients of returns to cumulative full-time, part-time, and nonworking experience and the unemployment rate are reported, leaving the full results in Appendix A.2. A formal test rejects the null hypothesis of exogenous sample selection at the conventional significance level.⁸ Since wages for the most recent (the 1970s) cohort are available only up to

⁸ Although not reported for brevity, all the main conclusions of the current paper remain valid even

Table 2.3: Estimation Results of Husband's Wage Equation

	1950s through 1970s
α_1	1.0000 (0.01837)
α_2	0.0431 (0.0012)
α_3	-0.00081 (0.00004)
α_4	-0.0027 (0.0025)

Source: The author's estimation using the PSID.

Robust standard error estimates are in parentheses.

The constant in the husband's wage equation is normalized as 1.

the mid-thirties, the wage function for the 1970s cohort is estimated based on a pooled sample between the 1960s and the 1970s cohort. This is a drawback of the current research, although, for the age range between 25 and 34, where wages are available for both the 1960s and 1970s cohorts, a formal test concludes that wage-age profiles are similar between the two cohorts. That said, the current paper focuses on the contrasting results between the 1950s and the 1960s cohort, as the change from the 1950s to the 1960s in the life-cycle labor supply behavior is much more dramatic than any other between-cohort changes.

Estimates in Table 2.4 suggest the following. First, estimated returns to full-time experience in the full-time sector are higher for the 1960s than the 1950s cohort. Even within the group of younger cohorts, full-timers of the more recent cohort (the 1970s) enjoy higher returns to past full-time experience than those of the 1960s cohort. Evaluated at the five years of cumulative full-time work experience, an additional year of full-time experience of a typical wife born in the 1950s is associated with a rise in real wages by 4.0 percent, with corresponding figures for the 1960s and the 1970s cohorts being 4.7 and 5.0, respectively. The tendency of observing greater returns to full-time experience for the younger cohort is still preserved even in the part-time sector. Consistent with Francesconi (2002), even in the part-time sector, estimated returns to full-time experience are generally greater than those to part-time experience.

Second, the estimated return to full-time experience in the full-time sector reaches the peak earlier for the younger than the older cohort. For the 1950s cohort, it reaches the peak at 26 years of full-time experience. Comparable figures for the 1960s and the 1970s

when I use the OLS results without correcting for the sample selectivity.

Table 2.4: Estimation Results of Wife's Wage Equation

	1950s	1960s	1970s
Initial Wage			
β_0	0.9044	0.8901	0.8811
Full-time			
β_1	0.0488	0.0602	0.0656
β_2	-0.00093	-0.00134	-0.00155
β_3	0.0280	0.0294	0.0335
β_4	-0.00209	-0.00360	-0.00361
β_5	-0.0511	-0.0775	-0.0772
β_6	0.00138	0.00276	0.0023
Part-time			
$\beta_1+\beta_7$	0.0431	0.0642	0.0790
$\beta_2+\beta_8$	-0.00099	-0.00217	-0.00249
$\beta_3+\beta_9$	0.0348	0.0365	0.0219
$\beta_4+\beta_{10}$	-0.00063	-0.00101	-0.00054
$\beta_5+\beta_{11}$	-0.0858	-0.1351	-0.1328
$\beta_6+\beta_{12}$	0.00230	0.00479	0.00510
Unemployment Rate			
β_{13}	-0.0218	-0.0288	-0.0332

Source: The author's estimation using the PSID.

The two-step estimation method suggested by Heckman (1979).

cohorts are 22 and 21, respectively. Similar patterns are observed regarding the estimated return to full-time experience in the part-time sector.

Third, when measured by wage losses during a nonworking period, the younger cohorts suffer from a greater rate of human capital depreciation than the older cohort. For example, other things being held constant, real wages of a typical married woman from the 1950s cohort working in the full-time sector tend to go down by 3.7 percent, after she experiences five years of a nonworking period, in comparison with 5.0 percent for the 1960s and 5.4 percent for the 1970s cohort. Comparable figures for someone working in the part-time sector are 6.3, 8.7 and 8.2 percent, respectively.

Fourth, the estimated gap between the return to full-time experience and the return to part-time experience is greater for the younger than the older cohort. For example, in the full time sector, the estimated return to an additional year of full-time experience for

someone who just enters the labor market is 4.8 percent for the 1950s cohort, whereas the comparable figure to part-time experience is 2.8 percent, resulting in a 2 percentage point gap between the two returns. For the 1960s cohort, respective figures are 6.0 percent, 2.9 percent, and 3.1 percentage points. The tendency of observing a greater gap between the two types of returns for younger cohorts is generally preserved in both sectors. All these observations imply that the opportunity cost of childbearing at the early stage of the life-cycle is higher for the younger than the older cohort, especially to full-timers. As will be demonstrated in Section 2.6, the increased opportunity cost for the younger cohorts plays the dominant role in explaining the dramatic changes from the older to younger cohorts in the life-cycle labor supply behavior.

As in most existing studies (e.g., Bils, 1985; Solon et al., 1994), real wages are significantly negatively affected by the contemporaneous unemployment rate. For example, a one point reduction in the aggregate unemployment rate leads to a rise in real wages of married women from the 1950s cohort of 2.2 percent. Comparable figures for the 1960s and the 1970s cohort are 2.9 and 3.3 percent, respectively.⁹

2.5 Model Calibration

2.5.1 Exogenous Parameters

Individuals live 10 periods ($T=10$), starting their lives at age 1 (a_1) as adults and ending at age 10. Each period (or ‘age’) consists of 5 years of actual ages, with a_1 representing actual ages of 25-29, a_2 30-34, ..., and a_{10} representing 70-74. Wives are subject to infertility from a_4 (40-44). And both husbands and wives retire at a_9 (65-69). Young mothers are defined by those who have the first child at a_1 (25-29) and old mothers are those who have the

⁹ Although higher estimated unemployment coefficients (in an absolute value) for women than for men seem at odds with some existing studies that report greater real wage procyclicality for men than women (e.g., Blank, 1989a; Tremblay, 1990; Solon et al., 1994), the current study is not directly comparable to existing ones for a number of reasons. Among others, unlike existing studies, I neither control for cyclically changing composition of work forces, nor detrend wage series. The current study also differs from existing ones in the sample period and specification of the empirical model. As noted by Abraham and Haltiwanger (1995), among others, measured real wage cyclicalities are quite different depending on the sample period adopted.

first child after a_1 . Newborn children are assumed to be attached to the household for 3 periods.¹⁰

Child care costs

Using the PSID, I estimate the child care cost function, specified by Ribar (1992, 1995).¹¹

$$m_{i,t} = c_1 + c_2 k_{i,t}^y + c_3 k_{i,t}^m + c_4 k_{i,t}^o + \epsilon_{i,t} \quad (2.10)$$

where the dependent variable is per hour child care cost of household i in year t , defined as the ratio of the total yearly child care costs to annual working hours, $k_{i,t}^y$ represents the number of children between the ages of 0 to 4, $k_{i,t}^m$ the number of children between the ages of 5 to 9, $k_{i,t}^o$ the number of children between the ages of 10 to 14, and $\epsilon_{i,t}$ is the error term. Given the age composition of children, the total child care cost is computed by the product of the predicted per hour child care cost (m) and working hours (n^w) (Ribar, 1992, 1995).

Table 2.5 reports estimation results of equation (2.10) for each cohort. For brevity, only estimated coefficients are reported along with their standard error estimates. Estimates show that child care becomes more costly with younger children ($c_2 > c_3 > c_4$). More importantly, little difference is observed across cohorts in the estimated coefficients.

Wages and human capital

Estimated equation (2.8) and (2.9) are used to predict the husband's and the wife's wages, respectively. Following existing studies (e.g., Attanasio et al., 2008), the husband's and

¹⁰ In the current study, the 1960s cohort, for example, is represented by those who were born between 1961 and 1965. All the other cohorts are defined in a similar fashion. This definition dovetails neatly with the five-year groupings of the age group. For example, as ages of the 1960s cohort reach 25 to 29 in 1990, time-varying labor supply determinants (taxes, business cycle conditions, etc) measured at that point-in-time (1990) are used to explain labor supply behaviors of the 1960s cohort in their late twenties. Similarly, the labor supply determinants measured in 1995 affect labor supply decisions of the 1950s cohort in their early thirties (30-34). In addition, allowing a five-year interval between two adjacent cohorts makes characteristics of the two cohorts more distinctive.

¹¹ His specification is simplified by excluding some explanatory variables that affect local child care utilization.

Table 2.5: Estimation Results of the Child Care Cost Function

Coef	1950s	1960s	1970s
c_1	0.3586 (0.0756)	0.3363 (0.1395)	0.3785 (0.1194)
c_2	0.3488 (0.0445)	0.3619 (0.0729)	0.3515 (0.0674)
c_3	0.1167 (0.0441)	0.1478 (0.0711)	0.1406 (0.0709)
c_4	-0.0649 (0.0448)	-0.0813 (0.0772)	-0.0889 (0.0872)

Source: The author's estimation using the PSID.

Per hour child care costs are normalized by the husband's initial wages.

Estimated standard errors are in parentheses.

the wife's wages are stochastic with permanent shocks, ν^h and ν^w , that have the following joint distribution:

$$\begin{aligned}
 \nu^w &= \nu_-^w + \xi^w \\
 \nu^h &= \nu_-^h + \xi^h \\
 \text{where } \xi &= (\xi^w, \xi^h) \sim N(\mu_\xi, \sigma_\xi^2) \\
 \mu_\xi &= \left(-\frac{\sigma_{\xi^w}^2}{2}, -\frac{\sigma_{\xi^h}^2}{2}\right) \quad \text{and} \quad \sigma_\xi^2 = \begin{pmatrix} \sigma_{\xi^w}^2 & \sigma_{\xi^w \xi^h} \\ \sigma_{\xi^h \xi^w} & \sigma_{\xi^h}^2 \end{pmatrix}.
 \end{aligned} \tag{2.11}$$

Following Hyslop (2001), the correlation between the two permanent shocks is 0.34. The standard deviation of the permanent shock to the husband's wages, σ_{ξ^h} , is 0.11 on an annual basis, which is borrowed from Low et al. (2010). Without enough information on the permanent shock to the wife's wages, I assume equality between the husband and the wife in the standard deviation of the permanent shock.

Taxes

A series of studies by Berliant and Gouveia (1993) and Gouveia and Strauss (1994) attempts to estimate the effective tax function which summarizes the characteristics of the income tax rate. The income tax is a mapping from a set of characteristics of income (wage income, dividends, capital gains, etc.) to tax liabilities (Arrow, 1980). Thus, without

detailed information about income tax characteristics, calculating the income tax is a difficult task. The effective tax function, however, allows me to compute average tax rates without considering those characteristics by relating the income tax liabilities to total income directly. Due to this advantage, several studies investigating the effects of taxes on women's labor supply (Erosa and Koreshkova, 2007; Kaygusuz, 2010; Gunner et al., 2012a,b) adopt the effective tax function for the income tax rate.

For the purpose of estimating the effective income tax function, I use the March CPS, which has reported various tax-related variables including federal income tax liability, state income tax liability, and adjusted gross income for the previous year since 1980.¹² For each household, the total income tax liability is computed as a sum of the federal and the state tax liability, and the income tax rate (τ_I) is defined by the ratio of the total income tax liability to the total adjusted gross income.¹³ In each year, the entire observations are classified by the income decile and the number of children.¹⁴ Then, in each classified subgroup, I calculate the average tax rate and the average household income. Finally, the following effective income tax function is estimated separately for each year:

$$(\tau_I)_{j,d} = \theta_0 + \theta_1 \ln(I_{j,d}) + \theta_2 k_j + \epsilon_{j,d} \quad (2.12)$$

where $(\tau_I)_{j,d}$ represents the average income tax rate in the j children- d^{th} decile group, $I_{j,d}$ the average income in the same group, k_j the number of children, and $\epsilon_{j,d}$ is the error term.

¹² These variables are not native to the CPS, but added by the Census based on IRS public use datasets. The Census constructs a tax model that uses the information collected from the March CPS as much as possible to form tax units and in essence fill out all of the necessary forms for these constructed units. A number of assumptions have been made along the way, and the March CPS data is supplemented by imputing data from IRS public use datasets in order to fill out the forms more completely. See Henry and Day (2005) for details on the concepts and the components of the income and tax variables in the March CPS.

¹³ In comparison, Kaygusuz (2010) and Gunner et al. (2012a,b) calculate the income tax rate as follows:

$$income\ tax\ rate = \frac{\left\{ \frac{total\ amount\ of\ income\ tax\ liability}{number\ of\ taxable\ returns} \right\}}{\left\{ \frac{total\ adjusted\ gross\ income}{number\ of\ returns} \right\}}$$

As the number of taxable returns and the number of returns are not available in the CPS, I assume that they are equal.

¹⁴ Kaygusuz (2010) does not consider the number of children, and Gunner et al. (2012a,b) assume cases of only 0 or 2 children. In order to consider the effects of the children-related tax credits on the average income tax rate more effectively, the current study uses more detailed cases when grouping the sample by the number of children: 0, 1, 2, and 3 or more.

Equation (2.12) is estimated by the Weighted Least Squares (WLS) with the weight being the square root of the sample size of each subgroup.

Table 2.6 provides estimated coefficients of the effective income tax function for each year. The reduction in the tax rate associated with the number of children (θ_2) is more substantial after 1995, as Per Child Tax Credit was first introduced in 1997, and Dependent Child Tax Credit was expanded after 2000. Consequently, the younger cohorts experience a greater reduction in tax rates with an additional child than the older cohort. For example, when women are at ages 25-29, an additional child leads to a reduction in the average tax rate by 0.47 percentage points for the 1950s cohort, 0.52 percentage points for the 1960s cohort, and 1.15 percentage points for the 1970s cohort. Corresponding figures for women at ages 30-34 are 0.32, 0.63, and 1.25 percentage points for the 1950s, 1960s, and the 1970s cohort, respectively.

Table 2.6: Estimation Results of Effective Income Tax Function

Year	θ_0	θ_1	θ_2
1980	-0.0228 (0.0081)	0.1111 (0.0048)	-0.0047 (0.0011)
1985	-0.0201 (0.0061)	0.0954 (0.0034)	-0.0032 (0.0012)
1990	-0.0241 (0.0058)	0.0923 (0.0032)	-0.0052 (0.0012)
1995	-0.0215 (0.0063)	0.0878 (0.0034)	-0.0063 (0.0012)
2000	-0.0240 (0.0076)	0.0901 (0.0040)	-0.0115 (0.0013)
2005	-0.0122 (0.0051)	0.0722 (0.0032)	-0.0125 (0.0013)
2010	-0.0292 (0.0050)	0.0815 (0.0030)	-0.0102 (0.0013)

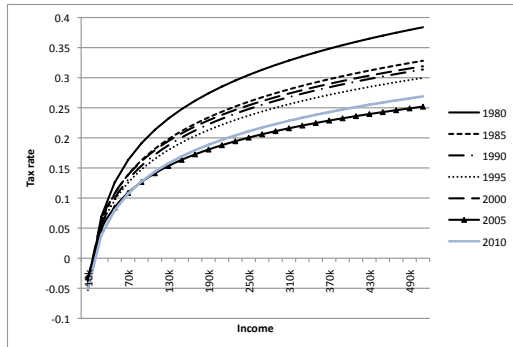
Source: The author's estimation using the March CPS.

Standard error estimates are in parentheses.

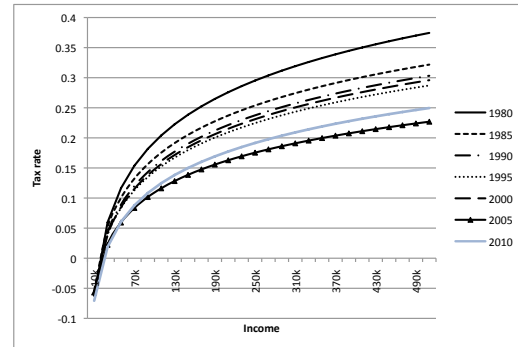
The income tax rate that is not associated with the children-related tax credits has generally decreased over time with several dramatic changes in the U.S. income tax structure.¹⁵ Figures 2.4a and 2.4b illustrate how predicted income tax rates have changed over time for the case of no children and that of two children, respectively. Estimates show that at each income level, predicted tax rates have generally decreased over time for both cases, with a greater reduction for the case of two children than no children. In the

¹⁵ See APPENDIX A.1 for details on the history of changes in the U.S. income tax structure.

model calibration, I use the estimates reported in Table 2.6 to calculate the total income tax liability for each household as a product of the predicted income tax rate and the total household income.



(a) Effective Income Tax Rates with No Children



(b) Effective Income Tax Rates with Two Children

Figure 2.4: Effective Income Tax Function

Finally, I use capital tax rates released from the Department of Treasury and payroll tax rates obtained from the Social Security Administration, as reported in Table 2.7. The capital tax rate has been variable, whereas the payroll tax rate has been stable over time.

Table 2.7: Capital and Payroll Tax Rates

Year	τ_k^a	τ_p^b
1980	0.168	$\min(I_n, 5.2177) \times 0.0613$
1985	0.154	$\min(I_n, 6.1093) \times 0.0705$
1990	0.225	$\min(I_n, 6.5155) \times 0.0765$
1995	0.246	$\min(I_n, 6.6662) \times 0.0765$
2000	0.198	$\min(I_n, 7.3457) \times 0.0765$
2005	0.148	$\min(I_n, 7.6498) \times 0.0765$
2010	0.138	$\min(I_n, 8.1060) \times 0.0765$

^a Data source: The Department of Treasury.

^b Data source: The Social Security Administration.

Business cycle conditions

Following existing studies (e.g., Aaronson et al., 2006), I also consider the effects of business cycle conditions on cohort labor supply behaviors. I use the unemployment rate as a cyclical indicator.¹⁶ In my model, exogenous changes in business cycle conditions affect the wife's and the husband's wages which are considered as important determinants of the wife's labor supply. Table 2.8 reports unemployment rates for selected years. These changes in business cycle conditions may affect labor supply behaviors of different cohorts at different stages of the life-cycle.

Table 2.8: Unemployment Rates

Year	Unemployment Rate
1980	7.1
1985	7.2
1990	5.6
1995	5.6
2000	4.0
2005	5.1
2010	9.6

Source: Bureau of Labor Statistics.

Other exogenous parameters

I set the per-period discount factor at 0.9, which corresponds to 0.98 of the annual discount rate. With the annual interest rate of 0.015, the per-period interest rate (r) is set at 0.077.¹⁷

¹⁶ In the literature of real wage cyclicality, the unemployment rate has been the most frequently used cyclical indicator, with real GDP being the next most. Aaronson et al. (2006) use the contemporaneous and lagged deviations of employment in the nonfarm business sector as a cyclical indicator. Boushey (2005) uses year dummies rather than actual unemployment rates or real GDP.

¹⁷ Attanasio et al. (2008) use the same values of the discount factor and the interest rate as the current study.

Table 2.9: Model Parameters Calibrated

	Parameter	1950s
RRA of consumption	γ	0.54
RRA of quality of children	λ	0.70
RRA of quantity of children	θ	0.38
Elasticity of substitution b/w $(\frac{m}{k})$ and $(\frac{1-n^w}{k})$	ϕ	0.70
Relative share of mother's time to market goods with children of ages 0 to 4	g^y	0.68
Relative share of mother's time to market goods with children of ages 5 to 9	g^m	0.49
Relative share of mother's time to market goods with children of ages 10 to 14	g^o	0.26
Child care production	δ	0.29
Disutility from work	η	-1.04

2.5.2 Calibrated Parameters

In order to identify the determinants whose changes explain why the younger cohorts show different labor supply behaviors from the 1950s cohort, I calibrate the model for the 1950s cohort first. The calibrated model is then used to account for how the 1950s cohort would behave if they experienced the same labor supply determinants as the younger cohorts. Important labor supply determinants are identified when the ‘would-be’ labor supply profiles of the 1950s cohort becomes close to the actual profile of the younger cohorts following changes in the determinants. A set of model parameters are selected to match a set of population characteristics described by data (henceforth target values) with the population characteristics generated by the model. The numerical method is explained in APPENDIX A.3. Included in the set of parameters to be calibrated are a coefficient of relative risk aversion of consumption (γ); coefficients of relative risk aversion of child care production (λ, θ); the elasticity of substitution between mother's time ($\frac{1-n^w}{k}$) and market goods ($\frac{mn^w}{k}$) on child care, which is $(1/(1 - \phi))$; the relative share of mother's child care time to child care market goods (g^y, g^m, g^o)¹⁸; the weight on child care production (δ);

¹⁸ As can be seen in Table 2.9 for definitions of g^y, g^m , and g^o , the relative share of mother's child care time to child care market goods is allowed to vary over children's ages. For example, mother's child care time is less needed when children grow older (Olivetti, 2006).

Table 2.10: Target Values vs. Model-Generated Values

Target	1950s	
	Data	Model
Per capita employment (25-34) ^a	0.596	0.600
Per capita employment (35-44) ^a	0.729	0.726
Per capita employment (45-49) ^a	0.772	0.765
Per capita employment of married women with children of ages 0 to 4 ^a	0.501	0.492
Number of children ^b	1.93	1.97
Share of nonmothers ^b	0.152	0.141
Age at first childbirth ^b	28.68	28.69
Share of old mothers ^b	0.219	0.230
Per capita full-time employment (25-49) ^a	0.508	0.512
Share of the wife's wage share spent on child care ^b	0.135	0.169

^a Source: March CPS

^b Source: June CPS

and the parameter governing the disutility from work (η). To pin down nine parameters in the utility function, I match ten target values from the data to ten corresponding model-generated moments. Included in the set of the target values are per capita employment for ages of 25-34, per capita employment for 35-44, per capita employment for 45-49, per capita employment of married women with children of ages between 0 and 4, the number of children that a wife has until 39, the share of nonmothers, the share of old mothers, the average age at first childbirth, per capita full-time employment for 25-49, and the share of the wife's wages spent on child care. Table 2.9 reports the set of model parameters calibrated and Table 2.10 compares the target values with corresponding values generated by the calibrated model.

2.6 Explaining Changes in Women's Life-Cycle Labor Supply Across Cohorts

On the basis of the results from Sections 2.4 and 2.5, this section identifies the determinants whose changes explain the dramatic changes from the older to the younger cohorts in the amount and patterns of the life-cycle labor supply: while life-cycle labor supply functions are bell-shaped for the older cohorts, they are roughly flat for the younger cohorts, and from the mid-thirties of the life-cycle, the younger cohorts continue to supply less labor than the older (1950s) cohort does. Basic strategies are as follows. I first examine how the model-generated life-cycle labor supply matches the observed labor supply of the 1950s cohort. Recognizing that my model fits the observed life-cycle labor supply behavior of the 1950s cohort to a reasonable degree, I examine which determinants are responsible for the dramatic changes from the 1950s cohort to the younger cohorts in the life-cycle labor supply behavior. This is done by replacing the values of labor supply determinants of the 1950s cohort by those of corresponding labor supply determinants of the younger cohorts. The fundamental research question at this stage is what the life-cycle labor supply profile of the 1950s cohort would be if the 1950s cohort had the same values of labor supply determinants as the younger cohorts, that is, if there were no between-cohort differences in the determinants of labor supply. A determinant is regarded as important when replacing its value by those of the younger cohorts makes the 'would be' labor supply profiles similar to the actual profiles of the younger cohorts. By doing this process for each determinant one by one and then for a combination of determinants, I identify, not only the set of determinants whose changes fully explain the dramatic changes in the life-cycle labor supply behavior, but also the most contributing determinant.

To summarize the main findings of this section, while the dramatic between-cohort changes in the life-cycle labor supply behavior are explained by a combination of changes in the opportunity cost of childbearing (as represented by between-cohort changes in returns to part-time and full-time experiences and the speed of human capital depreciation during a nonworking period), the children-related tax credits, business cycle conditions, and preferences, the opportunity cost is the dominant contributor. As previously stated, the increase in the opportunity cost makes the younger cohorts delay childbearing and

stay out of the labor force in subsequent stages of the life-cycle. To be specific, compared with the older cohort, the younger ones experience higher marginal returns to full-time work experience, an earlier peak in the wage-experience profile, lower returns to part-time experience, and higher rates of human capital depreciation during nonworking periods, all of which induce younger cohorts to pursue full-time work in the early stage of the life-cycle and delay childbirth. The relatively low returns to part-time experience tend to make the younger cohorts withdraw from the paid-market sector when they are separated from the full-time sector. Furthermore, due to the higher human capital depreciation rate for the younger cohorts, the probability of returning to the paid-market from the non-market is lower for younger cohorts than older ones. The results accord with those of existing studies (Eckstein and Wolpin, 1989; O'Neill and Polachek, 1993; Blau and Kahn, 1997; Francesconi, 2002; Olivetti, 2006) that examine the effects of returns to work experience on changes in women's labor supply. These points are elaborated in subsequent subsections.

2.6.1 Model-Generated Life-Cycle Labor Supply Behaviors

For the 1950s cohort, Figure 2.5 shows how the model-generated life-cycle labor supply (the solid line) matches the actual one observed from data (the dashed line). As evident in the figure, my model reasonably explains the actual life-cycle labor supply behavior of the 1950s cohort.

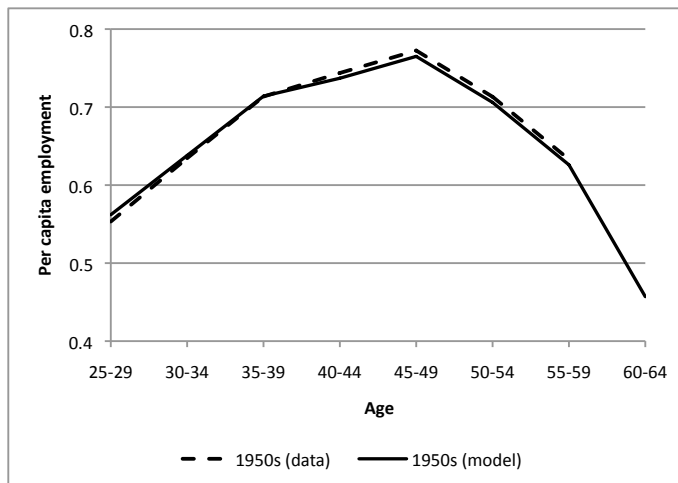


Figure 2.5: Calibration Results for the 1950s Cohort

2.6.2 Changes in the Opportunity Costs of Childbearing

Figures 2.6a and 2.6b explain how changes in the opportunity cost of childbearing are responsible for the dramatic changes from the 1950s to the 1960s and the 1970s cohort, respectively, in the labor supply behavior. The opportunity cost is represented by returns to full-time and part-time experiences and the speed of human capital depreciation during a nonworking period. In both figures, the dark solid line represents the model-generated life-cycle labor supply profile of the 1950s cohort, and the grey solid lines are the actual (observed) labor supply profiles of the 1960s and the 1970s cohorts. The dotted lines represent the ‘would-be’ labor supply curves of the 1950s cohort obtained by replacing only the opportunity cost in the labor supply function of the 1950s cohort by the opportunity cost of the 1960s or the 1970s cohort, leaving all the other determinants and preference parameters unchanged as those of the 1950s cohort. Comparison of the three profiles in each figure concludes that changes in the opportunity cost alone explain most of the changes in the labor supply behavior between the 1950s and the younger cohorts, as the dotted and the grey solid lines are very close to each other. To be specific, increased opportunity costs for the younger cohorts relative to the 1950s cohort make the younger cohorts supply more labor in earlier stages of the life-cycle and less in later stages of the life-cycle. There still remains some deviation of the dotted line from the grey solid line. In particular, the ‘would-be’ labor supply curve somewhat ‘overexplains’ the actual amount of labor supplied by the 1960s cohort from the early thirties. This overprediction is relatively more evident in the comparison of the 1950s and the 1970s cohort.¹⁹ Although the residual deviation requires a more precise tuning based on additional determinants, evidence in Figure 2.6 suggests that, if the older (1950s) cohort faced the same opportunity cost of childbearing as the younger cohorts, the older cohort would show similar labor supply behaviors as the younger cohorts do; however the increased opportunity cost for the younger cohorts relative to the older makes the younger cohorts supply more labor at the early stage and less at a later stage of the life-cycle and therefore makes the labor supply profile closer to

¹⁹ As previously observed, the CPS data show that the younger cohorts start to supply less labor than the 1950s cohort from their mid-thirties. In comparison, my model predicts that, if the older (1950s) cohort had the same opportunity cost as the younger cohorts, the older cohort would start to supply less labor than what is actually supplied by the older cohort from the early forties, requiring a more precise tuning based on additional determinants.

flat for the younger cohorts.

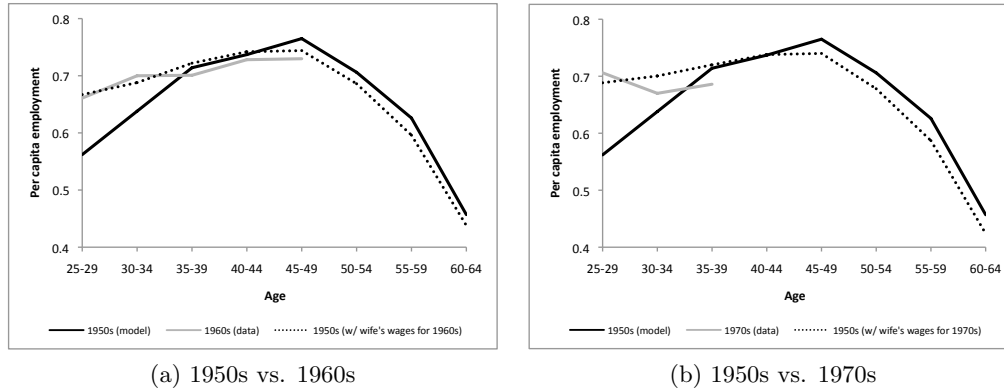
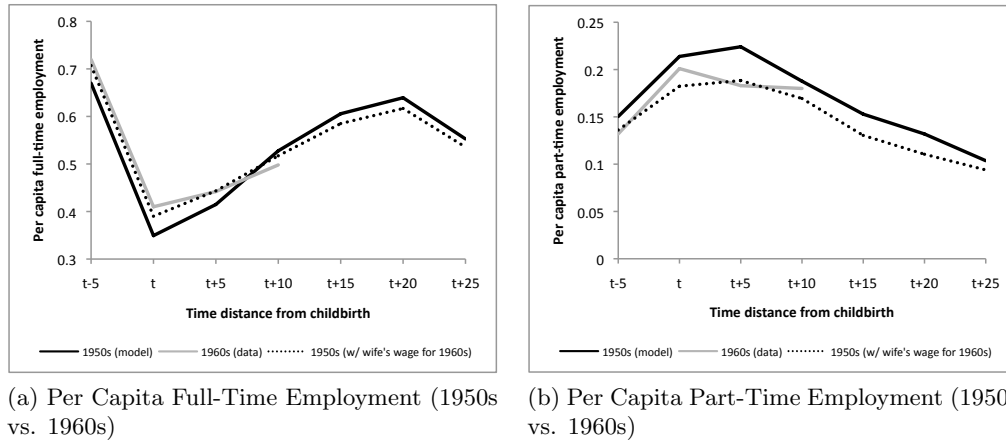


Figure 2.6: Effects of Changes in Opportunity Cost of Childbearing

Figures 2.7a through 2.7c further explain how the population share of each sector (full-time, part-time, and non-market) changes after childbirth, how changes in the sectoral distribution of married women are different between the older and the younger cohorts, and how the between-cohort difference is explained by changes in the opportunity cost of childbearing alone. I compare the 1950s cohort with the 1960s cohort for this purpose. In each figure, t represents the time of the first childbirth, the dark solid line represents the model-generated population share of each sector for the 1950s cohort, the grey solid line stands for the actual population share for the 1960s cohort, and the dotted line represents the ‘would-be’ share of each sector obtained by plugging the opportunity cost of the 1960s cohort into the labor supply function of the 1950s cohort. First, although not shown in the graph, my model predicts that, due to the increased opportunity cost of childbearing, the younger cohorts delay childbirth to later stages of the life-cycle. My model predicts that the share of old mothers, as previously defined, is 0.230 for the 1950s cohort, which increases to 0.286 (0.294) when the opportunity cost of the 1960s (1970s) cohort is plugged into the labor supply function of the 1950s cohort. In actuality, the share of old mothers is 0.282 (0.291) for the 1960s (1970s) cohort, implying that the increased opportunity cost of childbearing is mainly responsible for the delayed childbearing of the younger cohorts.²⁰

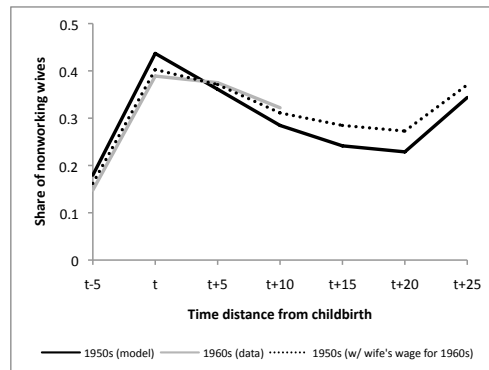
Second, as in Figure 2.7a, after childbirth, the population share of full-timers grows

²⁰ These numbers suggest that more than 100 percent of the increased share of old mothers from the 1950s



(a) Per Capita Full-Time Employment (1950s vs. 1960s)

(b) Per Capita Part-Time Employment (1950s vs. 1960s)



(c) Share of Non-Market Sector (1950s vs. 1960s)

Figure 2.7: Opportunity Cost of Childbearing and Sectoral Distribution of Married Women

to the younger cohorts is explained by the increased opportunity cost of childbearing. When I compute the model-generated average age at first childbirth for each cohort by a weighted average of age-group-specific cell means, it increases from 28.69 from the 1950s cohort to 29.18 for the 1960s and further to 29.29 for the 1970s cohort. In comparison, the model-generated shares of old mothers are 0.230, 0.291, and 0.310 for the 1950s, the 1960s, and the 1970s cohort, respectively. The increase in the average age at first childbirth is largely attributed to the dramatic increase in the share of old mothers, which is generally consistent with Mathews and Hamilton (2009). To compute the contribution of the increased opportunity cost of childbearing to the increased average age at first childbirth, I use the June Supplements to the CPS to compute the actual average age at first childbirth by the same weighted average method adopted in the model. The respective figures of 28.68, 29.15 and 29.21 for the 1950s, the 1960s and the 1970s cohort are very close to corresponding model-generated ones. When the opportunity cost of the 1960s (1970s) cohort is plugged into the labor supply function of the 1950s cohort, the 'hypothetical' average age for the 1950s cohort increases to 29.16 (29.22). Once again, these numbers suggest that more than 100 percent of the delayed childbearing is accounted for by the increased opportunity cost of child bearing from the older to

at a slower rate for the younger than the older cohort, which is mostly explained by the increased opportunity cost for the younger cohort. Readers can verify this by observing that the dotted line is very close to the grey solid line. Third, for the same reason, the share of the non-market sector shrinks at a slower rate for the younger than the older cohort for the next 20 years after childbirth (Figure 2.7c). Lastly, in Figure 2.7b, reflecting that the gap between the return to full-time experience and the return to part-time experience is greater for the younger cohort than for the older cohort (see Table 2.4), per capita employment in the part-time sector is always lower for the younger than the older cohort, which is also explained mostly by the increased opportunity cost of childbearing.

To examine whether the overall effects of changing opportunity costs on the life-cycle labor supply behavior come mainly from changing opportunity costs in the full-time sector or that in the part-time sector, I redo the analysis in Figure 2.6 by sector. In drawing hypothetical life-cycle labor supply functions (dotted lines) in Figures 2.8a and 2.8b, I assume that the 1950s cohort has the same wage structure only in the full-time sector as the younger cohorts (high returns to full-time work experience, low returns to part-time work experience, and the high rate of human capital depreciation in the full-time sector). Similarly, in constructing hypothetical labor supply functions in Figures 2.8c and 2.8d, I assume that the 1950s cohort has the same wage structure only in the part-time sector as the younger cohorts. Finally, in Figures 2.8e and 2.8f, hypothetical labor supply functions are derived under the assumption that the older cohort faces the same rate of human capital depreciation in both sectors as the younger cohorts do. As before, the dark solid lines and the grey solid lines represent the model-generated labor supply curves of the older cohort and the actual labor supply curves of the younger cohorts, respectively. In all cases, the resulting hypothetical labor supply profiles of the 1950s cohort become flatter relative to the actual profile of the 1950s cohort at least until the late forties. Nevertheless, the overall effect of changing opportunity costs on the labor supply behavior is dominated by the effect of changing opportunity costs in the full-time sector. This is easily verified by observing that the dotted line becomes even closer to the grey solid line in Figures 2.8a and 2.8b than in any other corresponding figures. Naturally, it is predicted that the higher opportunity costs of childbearing for the younger relative to the older cohorts in the full-time sector

the younger cohorts.

make the share of full-timers for the younger cohorts greater than that for the older cohort in the early stage of the life-cycle, which is supported by Figures 2.9a and 2.9b. In both figures, the dark solid line represents the share of full-timers for the 1950s cohort, and the grey solid lines are actual shares of full-timers for the younger cohorts. In comparison, the dotted lines represent the hypothetical shares of full-timers for the 1950s cohort under the assumption that the older cohort has the same wage structure in the full-time sector as the younger cohorts do. Focusing on Figure 2.9a, the 1960s cohort has a higher share of full-timers than the 1950s cohort until the late thirties, and a lower share from the early forties, which is mostly explained by the greater opportunity cost for the younger than the older cohort in the full-time sector. For the same reason, my model also predicts that proportionally more women delay childbirth among the younger cohorts than the older, as previously verified.²¹ With higher returns to full-time experience, with lower returns to part-time experience, and due to greater human capital depreciation associated with a nonworking period, it pays to work now as a full-timer, delay childbirth, and withdraw from the paid-market upon childbearing. In sum, the greatest contributing factor to the changing life-cycle labor supply behavior, that is, the increased opportunity cost of childbearing for the more recent cohort, comes mainly from the increased opportunity cost in the full-time sector.

2.6.3 Changes in Tax Rates

With the tax code that applies to the 1960s and the 1970s cohorts, which lowers tax rates of the younger cohorts below that of the 1950s cohort, the life-cycle labor supply of the 1950s cohort would increase by a small amount, as shown in Figures 2.10a and 2.10b. This seems at odds with existing studies (Bosworth and Burtless, 1992; Eissa, 1995; Erosa and Koreshkova, 2007; Kaygusuz, 2010; Gunner et al., 2012b) showing a substantial positive effect of a reduction in tax rates on married women's labor supply. These seemingly inconsistent results are not actually inconsistent when I consider the two opposing effects of the reduction in the income tax rate associated with an introduction of the new tax code

²¹ The share of old mothers for the 1950s cohort is 0.230 when I use the estimated coefficients of the wage function in the full-time sector for the 1950 cohort. When these coefficients are replaced by corresponding estimates for the 1960s, the share increases to 0.274. It increases further to 0.281 when they are replaced by the values for the 1970s cohort.

on women's labor supply. Since 1995, the reduction in tax rates has come not only from the reduced rates for income tax and capital gains tax but also from the introduction of Per Child Tax Credit and the increased Dependent Child Tax Credit, which raise the rate of tax deduction per child for the younger cohorts. Reduction in the general income tax rate increases women's labor supply, especially at the extensive margin, whereas the reduced tax rate associated with the introduction (for the 1960s cohort) and a further expansion (for the 1970s cohort) of Per Child Tax Credit along with an increased Dependent Child Tax Credit (mostly for the 1970s cohort) dampens participation incentives of married women and encourages the household to have more children. The younger cohort would have supplied more labor if the rate of tax deduction associated with Per Child Tax Credit and Dependent Child Tax Credit (hereafter referred to as the children-related tax credits) remained the same as the rate that the 1950s cohort experienced.

Figures 2.11a and 2.11b examine the effects of the children-related tax credits on the life-cycle labor supply. Consistent with my conjecture, if the rate of tax deduction of a more recent cohort were applied to the 1950s cohort, the 1950s cohort would reduce labor supply mostly during the late twenties and the thirties of the life-cycle. Additional calculation shows that, as the rate of tax deduction per child (θ_2 in the effective income tax function) increased from the 1950s cohort level to the 1960s and further to the 1970s level, the 1950s cohort would increase the number of children from 1.97 to 2.01 and further to 2.03. In fact, as shown in Figures 2.12a and 2.12b, under the assumption that per child tax deduction remains the same across cohorts at the 1950s level, the size of labor supply increase associated with reduction in the income tax rate from the older to the younger cohorts is greater than what is observed in Figures 2.10a and 2.10b.

2.6.4 Changes in Business Cycle Conditions

Changes in business cycle conditions have some effects on between-cohort changes in the labor supply behavior, which is generally consistent with the results of Boushey (2005) and Aaronson et al. (2006).²² The 1950s cohort has experienced a continuous decrease in the unemployment rate over the course of the life-cycle (at least until the mid-fifties),

²² Hotchkiss (2006), however, finds that the contribution of the business cycle effects to the reduction of women's labor supply between 2000 and 2005 is almost negligible.

while younger cohorts have experienced high unemployment rates in their late thirties and the forties due to the Great Recession. The wage cuts associated with the increased unemployment rate make women reduce labor supply. This is shown in Figure 2.13a and 2.13b, where the 1950s cohort would reduce labor supply from the late forties and the late thirties if faced with the same business cycle conditions as the 1960s and the 1970s cohort, respectively.

2.6.5 Changes in Child Care Costs

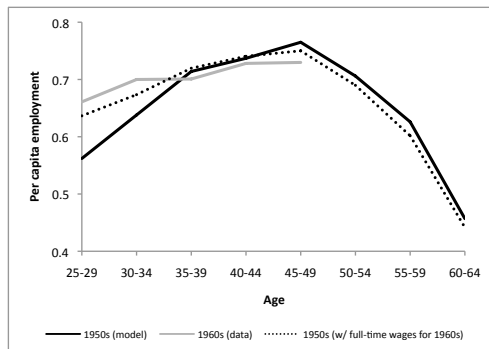
As revealed in Figures 2.14a and 2.14b, the effects of changes in child care costs on the labor supply behavior are almost negligible, which seems inconsistent with existing studies (Blau and Robins, 1988; Martinez and Iza, 2004; Attanasio et al., 2008). This is because the younger cohorts no longer experience a reduction in child care costs, which their predecessors experienced in the past. The current PSID sample produces that the median ratio of child care costs to the wife's earnings is 13.5 percent for the 1950s cohort, 14.2 percent for the 1960s cohort, and 13.9 percent for the 1970s cohort.

2.6.6 Contribution of Each Determinant to Between-Cohort Changes in Life-Cycle Labor Supply

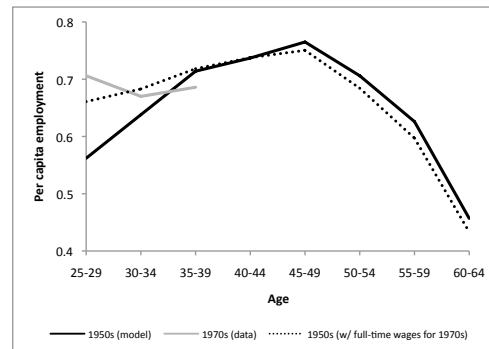
Tables 2.11 and 2.12 conduct a quantitative assessment of how each determinant contributes to the dramatic changes from the older to the younger cohorts in the life-cycle labor supply profile. For this purpose, I compare the older (1950s) and the younger cohorts in the amount of labor supplied at three different stages of the life-cycle: the late twenties (25-29), late thirties (35-39), and late forties (45-49). As emphasized repeatedly, compared with the 1950s cohort, the younger cohorts supply more labor in the early stage but supply less labor from the late (mid) thirties of the life-cycle. As the amount of labor supplied at the late thirties is relatively similar between the older and the younger cohorts, Tables 2.11 and 2.12 focus on the quantitative explanation of why the younger cohorts supply more labor than the older in the late twenties, but less in the late forties. At each stage, numbers in column *A* represent the amount of model-generated labor supply of the 1950s cohort, those in column *B* represent the amount of actual labor supply of the 1960s (or the 1970s) cohort, and those in column *C* stand for the amount of model-generated labor supply

of the 1950s cohort obtained by replacing a determinant in the labor supply function of the 1950s cohort by the corresponding determinant of the 1960s (or the 1970s) cohort. For each determinant, the closer the number in column C is to that in B , the greater the contribution of the determinant becomes to the gap between the younger and the older cohorts in the amount of labor supply. In the last column of each life-cycle stage, I compute the contribution (in percentage) of each determinant to the between-cohort gap in the amount of labor supply. For example, in Table 2.11, per capita employment at the early stage of the life-cycle (25-29) is higher for the 1960s cohort (0.661) than the 1950s cohort (0.562), resulting in a between-cohort gap of 0.099 points. At the same stage of the life-cycle, my model predicts that the 1950s cohort would increase its labor supply from 0.562 to 0.667 if it had the same opportunity cost of childbearing as the 1960 cohort. The resulting ‘would-be’ increase in the labor supply (0.105 points) accounts for 106 percent of the observed gap (0.099): more than 100 percent of the dramatic increase from the 1950s to the 1960s cohort in the amount of labor supplied at the late twenties of the life-cycle is explained by the increased opportunity cost between the two cohorts. As shown in the first four columns of Table 2.12, the opportunity cost is also the dominant contributor to the large gap between the 1970s and the 1950s cohort in the amount of labor supplied at the late twenties: 88 percent of the gap (0.144) is accounted for by the higher opportunity cost for the 1970s cohort relative to the 1950s. The increased opportunity cost of childbearing is also a major explanation of why the 1960s cohort supplies less labor than the 1950s cohort at the late forties of the life-cycle. As shown in the last four columns of Table 2.11, 60 percent of the reduction from the 1950s to the 1960s cohort in the amount of labor supplied at the late forties (45-49) is explained by the higher opportunity cost for the 1960s relative to the 1950s cohort. In this case, between-cohort changes in business cycle conditions also play some role in explaining the reduction (about 40 percent).²³

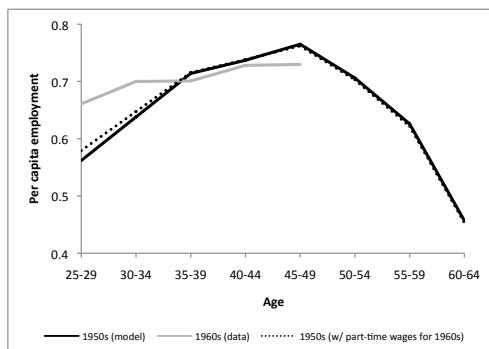
²³ I do not attempt to explain the labor supply gap between cohorts at 35-39, as the gap is relatively small.



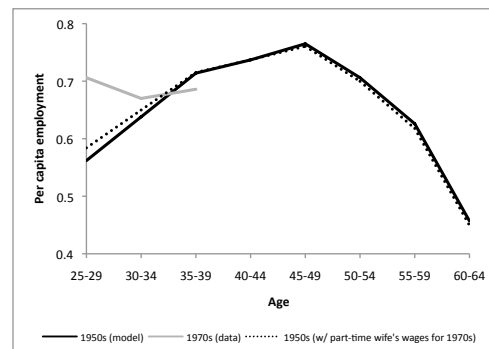
(a) Wages in Full-Time Sector (1950s vs. 1960s)



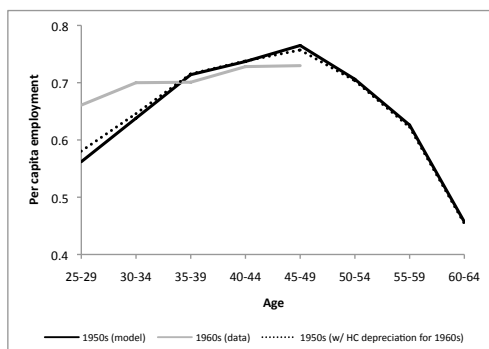
(b) Wages in Full-Time Sector (1950s vs. 1970s)



(c) Wages in Part-Time Sector (1950s vs. 1960s)



(d) Wages in Part-Time Sector (1950s vs. 1970s)



(e) Human Capital Depreciation (1950s vs. 1960s)



(f) Human Capital Depreciation (1950s vs. 1970s)

Figure 2.8: Effects of Changes in Opportunity Cost of Childbearing by Component

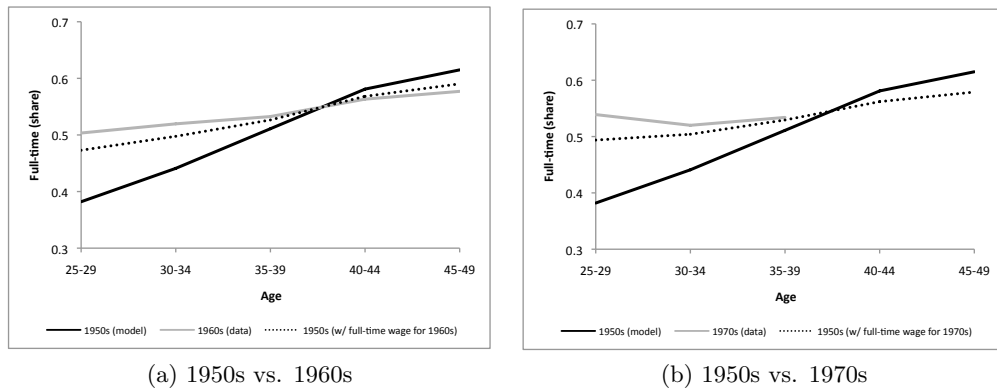


Figure 2.9: Opportunity Cost of Childbearing and Population Share of Full-Time Sector

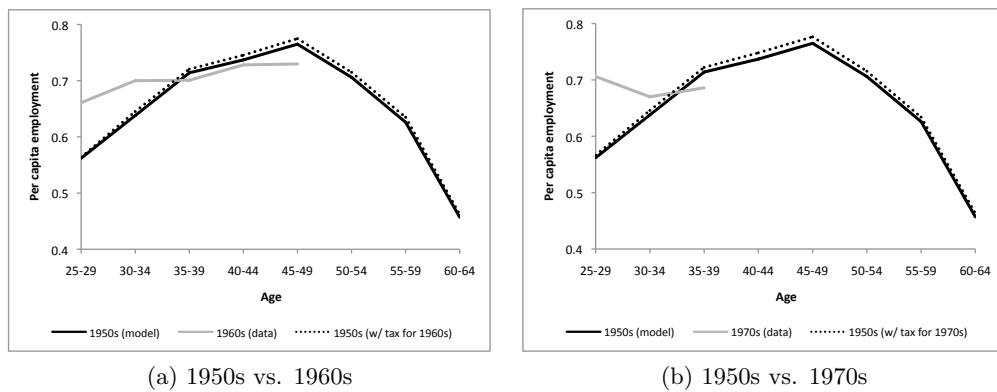


Figure 2.10: Effects of Changes in Tax Rates

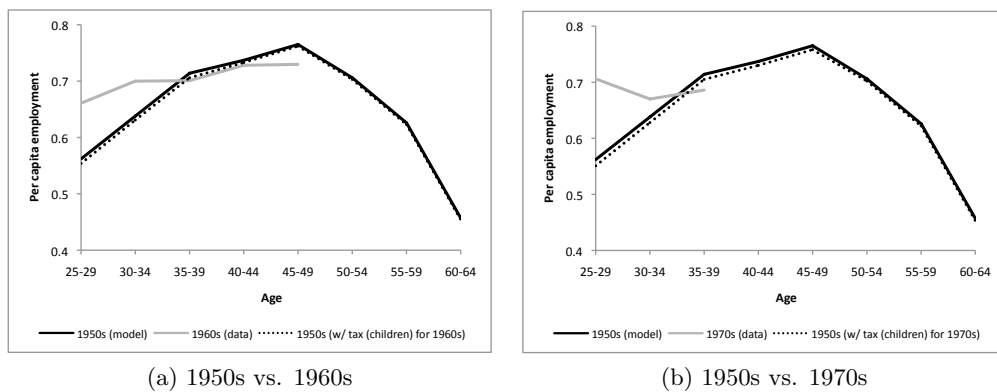


Figure 2.11: Effects of Changes in Tax Rates Associated with Children-Related Tax Credits

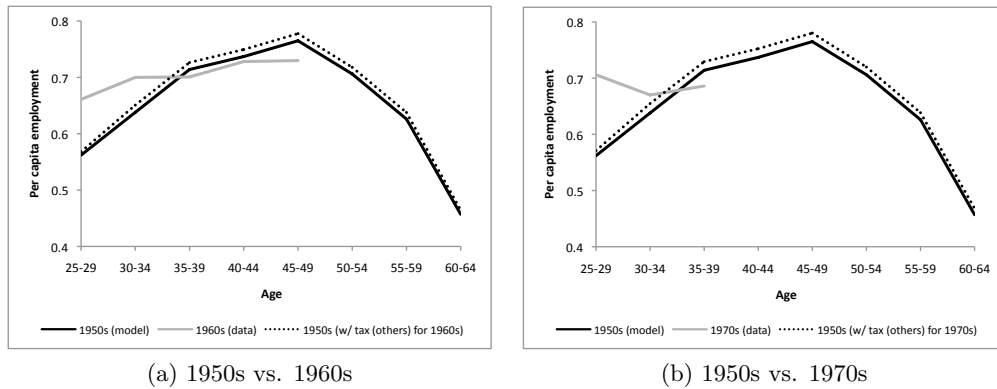


Figure 2.12: Effects of Changes in Tax Rates Independent of Children-Related Tax Credits

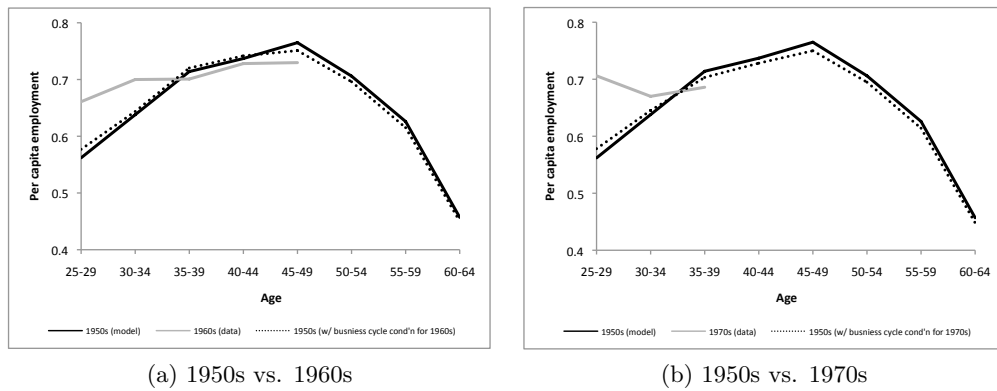


Figure 2.13: Effects of Changes in Business Cycle Conditions

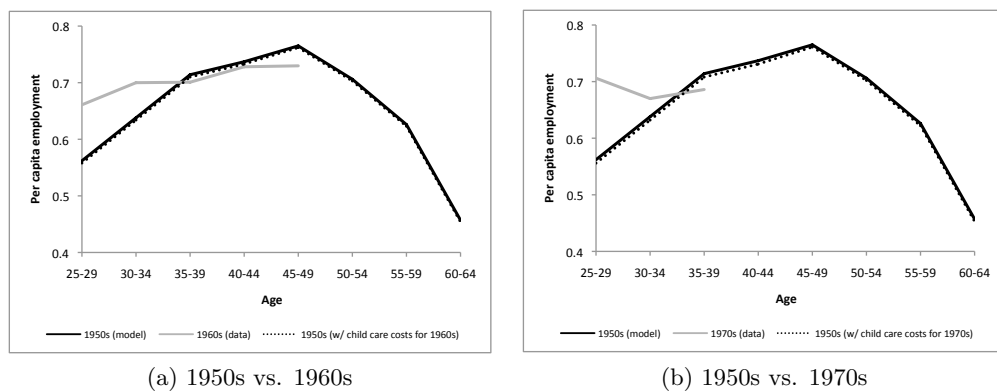


Figure 2.14: Effects of Changes in Child Care Costs

Table 2.11: Contribution of Each Determinant to Between-Cohort Changes in Amount of Labor Supply at Different Stages of Life-Cycle

	25-29			35-39			45-49		
	A	B	$\frac{C-A}{B-A} \times 100$	A	B	$\frac{C-A}{B-A} \times 100$	A	B	$\frac{C-A}{B-A} \times 100$
Opp. cost of childbearing	0.562	0.661	0.667	0.714	0.701	0.722	0.765	0.730	0.744
Children-related t-credits	0.562	0.661	0.554	0.714	0.701	0.706	0.765	0.730	0.762
Business cycle conditions	0.562	0.661	0.577	0.714	0.701	0.720	0.765	0.730	0.751
Child care costs	0.562	0.661	0.558	0.714	0.701	0.710	0.765	0.730	0.762
Other t-rates	0.562	0.661	0.568	0.714	0.701	0.723	0.765	0.730	0.777

A represents the amount of model-generated labor supply of the 1950s cohort.

B represents the amount of actual supply of the 1960s cohort.

C represents the amount of model-generated labor supply of the 1950s cohort with a 1960s cohort's determinant.

Table 2.12: Contribution of Each Determinant to Between-Cohort Changes in Amount of Labor Supply at Different Stages of Life-Cycle

	25-29			35-39		
	A	B	$\frac{C-A}{B-A} \times 100$	A	B	$\frac{C-A}{B-A} \times 100$
Opp. cost of childbearing	0.562	0.706	0.689	0.714	0.686	0.720
Children-related t-credits	0.562	0.706	0.552	0.714	0.686	0.707
Business cycle conditions	0.562	0.706	0.578	0.714	0.686	0.703
Child care costs	0.562	0.706	0.556	0.714	0.686	0.708
Other t-rates	0.562	0.706	0.571	0.714	0.686	0.727

A represents the amount of model-generated labor supply of the 1950s cohort.

B represents the amount of actual labor supply of the 1970s cohort.

C represents the amount of model-generated labor supply of the 1950s cohort with a 1970s cohort's determinant.

2.6.7 A Combination of Changes in the Determinants

As revealed in the previous discussion, changes in the opportunity cost of childbearing are the dominant contributor to the dramatic change from the older to the younger cohorts in the life-cycle labor supply behavior. When changes in the children-related tax credits are additionally considered in Figures 2.15a and 2.15b, the ‘would-be’ labor supply curves of the 1950s cohort are shifted down slightly and become closer to the actual labor supply profiles of the younger cohorts. As changes in business cycle conditions are additionally included in the analysis, the hypothetical labor supply profile of the 1950s becomes even closer to the actual profile of the 1960s cohort, as shown in Figure 2.16a. In explaining differences between the 1950s and the 1970s cohorts in the labor supply behavior (Figure 2.16b), additional consideration of changes in business cycle conditions would make the 1950s cohort supply more labor in the late twenties and less from the late thirties, making the hypothetical labor supply profile even flatter until the forties. Little change is observed when changes in child care costs are additionally reflected in the analysis (Figures 2.17a and 2.17b). With the additional consideration of changes in the tax code other than the children-related tax credits (Figures 2.18a and 2.18b), the older cohort would increase labor supply slightly over the course of their life-cycle.

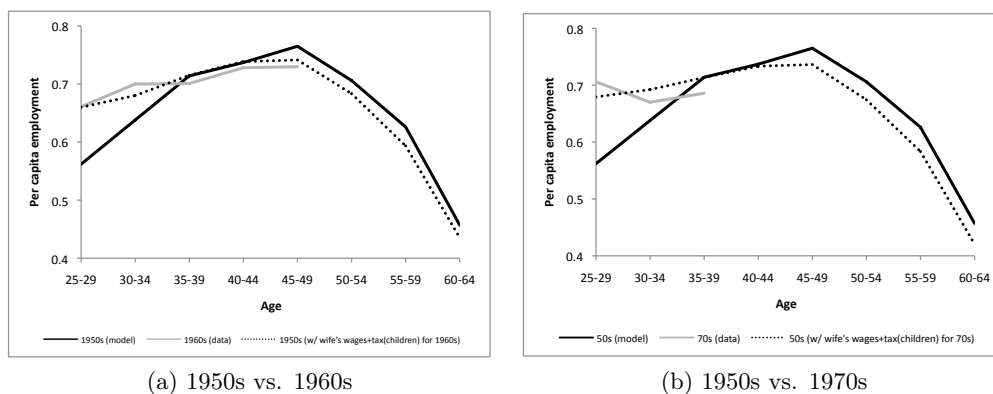


Figure 2.15: Effects of Changes in the Combination of Opportunity Costs of Childbearing and Children-Related Tax Credits

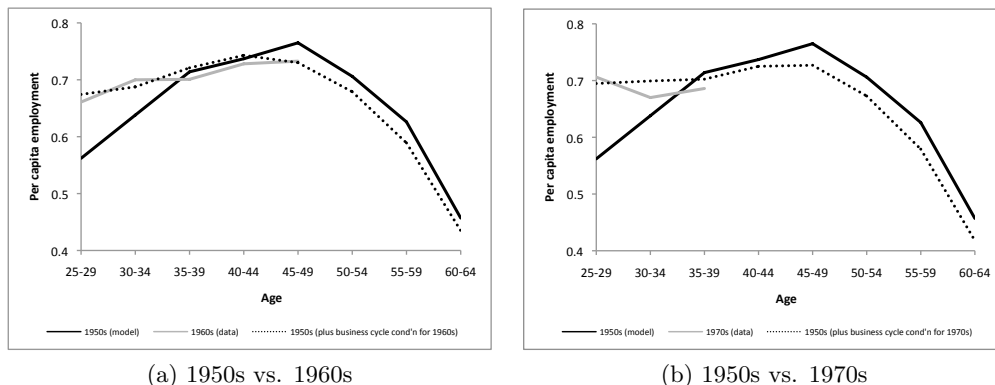


Figure 2.16: Effects of Changes in the Combination of Determinants in Fig. 2.15 and Business Cycle Conditions

2.6.8 Considering Changes in Preferences

Results in Figures 2.18a and 2.18b are not entirely satisfactory, as the combined effects of changes in various determinants do not fully explain the between-cohort changes in the labor supply profile. In particular, the model does not present a full explanation of why the younger cohorts supply less labor than the 1950s cohort from the late thirties. I therefore re-calibrate the model for the 1960s and the 1970s cohort to see if there are fundamental changes in preferences between the older and the younger cohorts. Table 2.13 reports two sets of model parameters calibrated for the 1960s and the 1970s, and, for each cohort, Table 2.14 compares the target values with corresponding values generated by the calibrated model. Comparison of figures in Table 2.13 with those in Table 2.9 reveals that calibrated model parameters are somewhat changed from the older to the younger cohorts. The younger cohorts, especially the youngest cohort (1970s) has a faster decreasing marginal utility of consumption (higher γ) and greater disutility of work (higher η) than predecessors. Also they have a greater relative share of mother's time to market goods (g^m , g^o) and a greater substitutability between mother's time and market goods (smaller ϕ) in the child care production function. And the marginal utility of an additional child decreases faster (higher θ) for the most recent cohort.

Before I examine whether these changes in preferences are responsible for the residual deviation observed in Figure 2.18, I use Figures 2.19a and 2.19b to show how the current

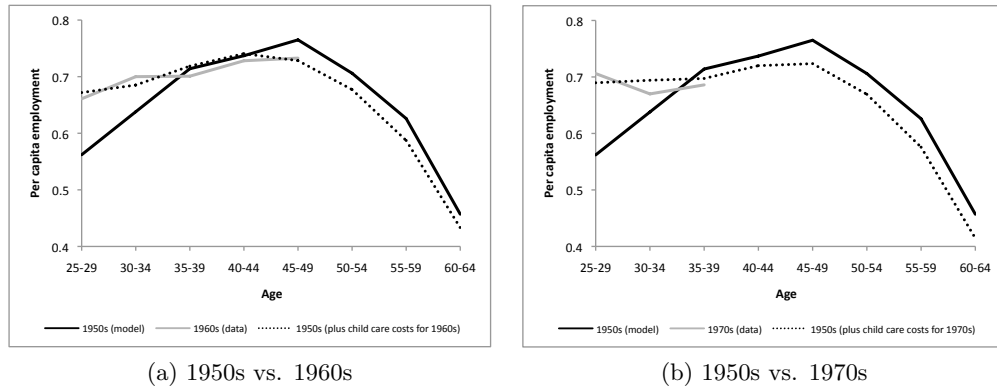


Figure 2.17: Effects of Changes in the Combination of Determinants in Fig. 2.16 and Child Care Costs

calibrated model performs well in predicting the actual behavior of the younger cohorts. Overall, the model predicts the actual life-cycle profiles of the 1960s and the 1970s cohort to a reasonable degree. For the 1960s cohort, the actual life-cycle profile (grey solid line) accords with the model-generated profile (dark dashed line) until the late forties. For the 1970s cohort, the two profiles are consistent even in that the amount of labor supply is reduced from the late twenties to the early thirties.

Figures 2.20a and 2.20b explain how the residual deviation observed in Figure 2.18 is explained by between-cohort changes in preferences. As usual, the dotted line represents the ‘would-be’ life-cycle profile of the 1950s cohort derived under the assumption that the 1950s cohort has the same values of the model parameters that the younger cohorts have. The results show that the ‘would-be’ and the actual profiles overlap to a reasonable degree, implying that most of the residual deviation observed in Figure 2.18 is explained by between-cohort changes in preferences.

Tables 2.15 and 2.16 provide a quantitative explanation of how changes in a combination of determinants and preferences explain the dramatic between-cohort changes in the labor supply behavior. As before, I focus on why the younger cohorts supply more labor than the older in the late twenties, but less in the late forties. As emphasized previously, the increased opportunity cost of childbearing is the dominant contributor to the observed change in the labor supply behavior. To repeat, about 100 percent of the increase in per capita employment from the 1950s to the 1960s at the late twenties of the life-cycle is

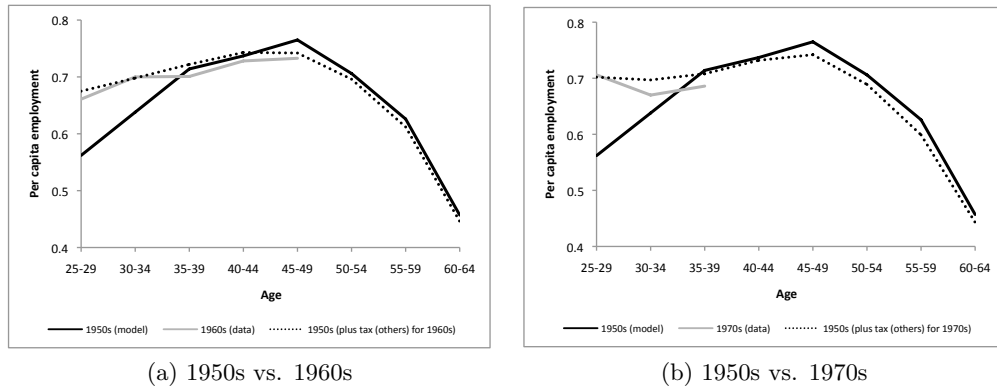


Figure 2.18: Effects of Changes in the Combination of Determinants in Fig. 2.17 and Other Tax Rates

explained by the increased opportunity cost of childbearing between the two cohorts, and the corresponding figure between the 1950s and the 1970s cohort is 88 percent. At the late forties of the life-cycle, about 60 percent of the reduction of labor supply from the older to the younger cohort is also explained by the increased opportunity cost of childbearing. The residual changes from the older to the younger cohorts in the amount of labor supply that is not explained by the increased opportunity cost are accounted for by a combination of changes in the children-related tax credits, business cycle conditions, and preferences, among others.²⁴

²⁴ As (relative to the 1950s cohort) the 1970s cohort changed its preferences to a greater extent than the 1960s did, changes in preferences are expected to play a greater role in explaining the residual deviation between the 1950s and the 1970s cohort than between the 1950s and the 1960s, as observed in Figure 2.18. Although Tables 2.11, 2.12, 2.15, and 2.16 do not report a contribution of determinant changes to between-cohort changes in the amount of labor supplied at the late thirties (because labor supply changes are relatively small at this stage), estimates in the last row of Table 16 show that the reduction in labor supply from the 1950s to the 1970s cohort, albeit not large, is mostly explained by changes in preferences between the two cohorts.

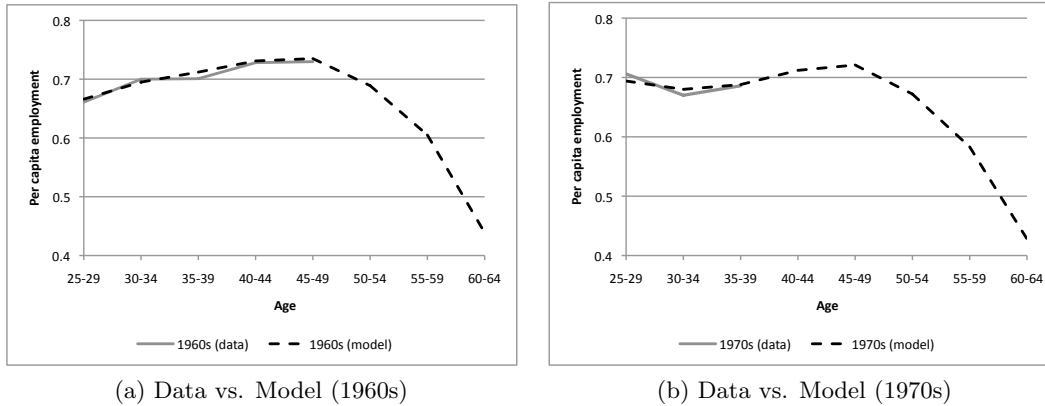


Figure 2.19: Calibration Results for the Younger Cohorts

Table 2.13: Model Parameters Calibrated

	Parameter	1960s	1970s
RRA of consumption	γ	0.55	0.59
RRA of quality of children	λ	0.71	0.71
RRA of quantity of children	θ	0.40	0.42
Elasticity of substitution b/w $(\frac{m}{k})$ and $(\frac{1-n^w}{k})$	ϕ	0.70	0.67
Relative share of mother's time to market goods with children of ages 0 to 4	g^y	0.68	0.69
Relative share of mother's time to market goods with children of ages 0 to 4	g^m	0.50	0.53
Relative share of mother's time to market goods with children of ages 0 to 4	g^o	0.27	0.30
Child care production	δ	0.28	0.28
Disutility from work	η	-1.11	-1.25

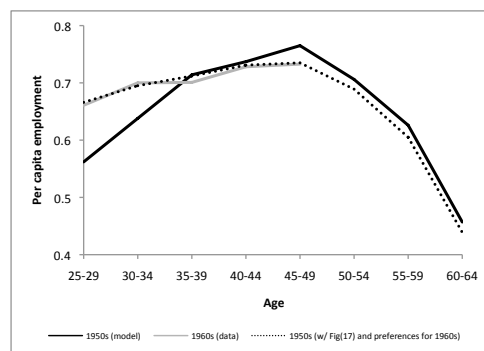
Table 2.14: Target Values vs. Model-Generated Values

Target	1960s		1970s ^c	
	Data	Model	Data	Model
Per capita employment (25-34) ^a	0.682	0.681	0.686	0.687
Per capita employment (35-44) ^a	0.720	0.722	0.686	0.687
Per capita employment (45-49) ^a	0.730	0.736	-	-
Per capita employment of married women with children ages 0 to 4 ^a	0.551	0.573	0.573	0.582
Number of children ^b	1.98	2.08	2.00	2.12
Share of nonmothers ^b	0.143	0.132	0.141	0.128
Age at first childbirth ^b	29.15	29.18	29.21	29.29
Share of old mothers ^b	0.282	0.291	0.291	0.310
Per capita full-time employment (25-49) ^a	0.536	0.541	0.531	0.542
Share of the wife's wage share spent on child care ^b	0.142	0.172	0.139	0.176

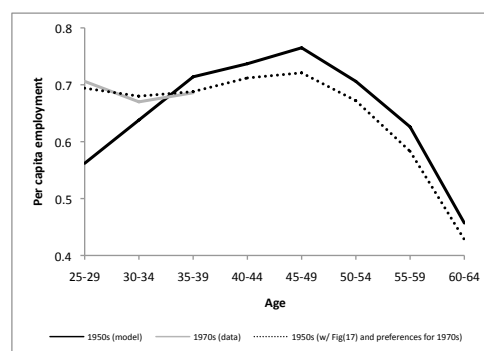
^a Source: March CPS

^b Source: June CPS

^c For the 1970s cohort, ages of a sample are between 25 and 39.



(a) 1950s vs. 1960s



(b) 1950s vs. 1970s

Figure 2.20: Effects of Changes in the Combination of Determinants in Fig. 2.18 and Preferences

Table 2.15: Contribution of Combination of Various Determinants to Between-Cohort Changes in Amount of Labor Supply at Different Stages of Life-Cycle

	25-29			35-39			45-49		
	A	B	$\frac{C-A}{B-A} \times 100$	A	B	$\frac{C-A}{B-A} \times 100$	A	B	$\frac{C-A}{B-A} \times 100$
(1) Opp. cost of childbearing	0.562	0.661	0.667	0.714	0.701	0.722	0.765	0.730	0.744
(2) Combination of (1) and children-related t-credits	0.562	0.661	0.660	0.714	0.701	0.715	0.765	0.730	0.741
(3) Combination of (2) and business cycle conditions	0.562	0.661	0.674	0.714	0.701	0.721	0.765	0.730	0.730
(4) Combination of (3) and child care costs	0.562	0.661	0.672	0.714	0.701	0.719	0.765	0.730	0.728
(5) Combination of (4) and other t-rates	0.562	0.661	0.674	0.714	0.701	0.728	0.765	0.730	0.741
(6) Combination of (5) and preferences	0.562	0.661	0.666	0.714	0.701	0.712	0.765	0.730	0.735

A represents the amount of model-generated labor supply of the 1950s cohort.

B represents the amount of actual labor supply of the 1960s cohort.

C represents the amount of model-generated labor supply of the 1960s cohort with the 1950s cohort's determinants.

Table 2.16: Contribution of Combination of Various Determinants to Between-Cohort Changes in Amount of Labor Supply at Different Stages of Life-Cycle

	25-29			35-39		
	A	B	$\frac{C-A}{B-A} \times 100$	A	B	$\frac{C-A}{B-A} \times 100$
(1) Opp. cost of childbearing	0.562	0.706	0.689	0.714	0.686	0.720
(2) Combination of (1) and children-related t-credits	0.562	0.706	0.679	0.714	0.686	0.714
(3) Combination of (2) and business cycle conditions	0.562	0.706	0.695	0.714	0.686	0.702
(4) Combination of (3) and child care costs	0.562	0.706	0.690	0.714	0.686	0.697
(5) Combination of (4) and other t-rates	0.562	0.706	0.703	0.714	0.686	0.708
(6) Combination of (5) and preferences	0.562	0.706	0.694	0.714	0.686	0.688

A represents the amount of model-generated labor supply of the 1950s cohort.

B represents the amount of actual labor supply of the 1970s cohort.

C represents the amount of model-generated labor supply of the 1950s cohort with the 1970s cohort's determinants.

2.7 Explaining the Recent Decline in Married Women's Labor Supply

Having found the major determinant of between-cohort changes in the life-cycle labor supply, in this section, I provide a quantitative explanation of the recent decline in the aggregate labor supply of married women, which is the unique feature of this study. It is believed that the same determinants that explain between-cohort changes in the labor supply behavior also explain the recent episode. This is so because at a point in time, the total labor supply is viewed as an aggregation of cohort-specific labor supplies, and as stated repeatedly, focusing on the mid-thirties and later stages of the life-cycle, each successive older cohort supplied more labor than the previous one until the 1950s cohort, after which the younger cohorts start to supply less labor than the immediate predecessor.

The following analytical steps are adopted to investigate how much of the reduction in the aggregate labor supply is explained by changes in which determinant. Since the model predicts the actual life-cycle profile of each cohort reasonably, at a point in time, I first aggregate cohort-specific labor supplies, weighted by population shares, to obtain the model-generated aggregate labor supply.²⁵ This is done for every five years²⁶ starting from 1980, which is the first year the 1950s cohort enters the labor market as prime age workers.²⁷ Confirming that this model-generated aggregate labor supply curve matches the actual labor supply very closely, I derive a pseudo aggregate labor supply curve for the same years under the assumption that the 1960s and the 1970s cohort supply the same amount of labor at each stage of the life-cycle as the 1950s cohort does. This is the case

²⁵ In the aggregation process, I use model-generated cohort-specific labor supply functions for the 1950s, 1960, and the 1970s cohort, but actual ones for earlier cohorts. This is because the current paper focuses on the dramatic changes in labor supply behaviors that occurred between the 1950s and more recent cohorts. In light of the discussion in Section 2.6, one might use actual profiles for the 1960s and the 1970s cohort in the aggregation process. Using model-generated profiles even for the two recent cohorts, however, allows me a complete decomposition of the recent decline by the contribution of each determinant. In addition, it helps me to predict the future movement of aggregate labor supply attributable to changes in determinants, say, recovery from the current recession.

²⁶ This dovetails neatly with the five-year groupings of the age group.

²⁷ The 1980s cohort is excluded from the aggregation process mainly for two reasons. First, exclusion of the 1980s cohort does not affect the outcome much as only the 25-29 age group can be involved in the analysis. Second, with the limited age group, estimation of the cohort-specific wage equation is extremely difficult.

when the 1960s and the 1970s cohort have the same values of determinants and preference parameters as the 1950s cohort: no behavioral change.

In this set-up, whatever differences that are observed from the comparison of the model-generated aggregate labor supply (henceforth actual labor supply curve) and the model-generated pseudo aggregate labor supply (henceforth pseudo labor supply curve) are attributed to changes from the 1950s cohort to the more recent cohorts in the set of labor supply determinants and preference parameters mentioned in the previous section. It should be kept in mind that, from the mid-thirties of the life-cycle, the younger cohorts start to supply less labor than the 1950s cohort, and changes in the opportunity cost of childbearing explain most of the behavioral changes. Consequently, it is believed that the same factor will explain the deviation of the actual labor supply from the pseudo labor supply curve. Finally, for the purpose of evaluating the contribution of each determinant to the recent decline in the aggregate labor supply, I use the values of the determinant for the younger cohorts in generating the ‘would be’ life-cycle labor supply curves of the 1950s cohort (leaving the values of all the other determinants and preference parameters the same as those for the 1950s cohort), aggregate the resulting cohort labor supply curves (actual ones up to the 1950s cohort and ‘would be’ ones for the 1960s and the 1970s), and compare the ‘hypothetical’ aggregate labor supply curve with actual and pseudo labor supply curves.

2.7.1 Actual vs. Pseudo Aggregate Labor Supply

Figure 2.21 compares the actual labor supply curve observed from data and the ‘actual’ labor supply curve generated by the model. The results show that my model predicts the observed quantity and patterns of aggregate labor supply to a reasonable degree, which is not surprising given that the model-generated cohort labor supply profiles are very close to observed ones, as shown in the previous section. For this reason, the model-generated labor supply curve is called the actual labor supply.

Now Figure 2.22 contrasts the actual (the dark solid line) with the pseudo labor supply curve (the grey solid line). First, the pseudo labor supply continues to increase until 2010, whereas the actual one declines during the 2000s. Second, from the mid-1980s through the late 2000s, the pseudo labor supply curve is located below the actual one. These two

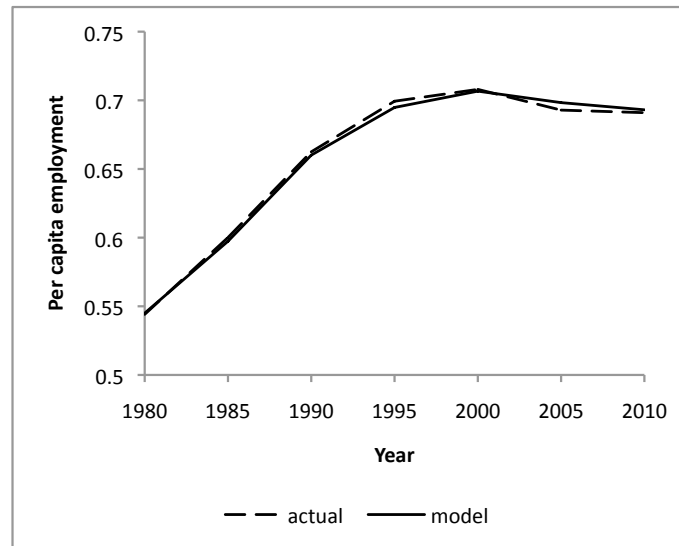


Figure 2.21: Aggregate Per Capita Employment Over Time (Actual vs. Model)

observations are easily understood when I consider that, compared with the 1950s cohort, the younger ones supply more labor at the early stage of the life-cycle, and less from the mid-thirties. Consequently, assuming that the younger cohorts supply the same amount of labor at each stage of the life-cycle as the 1950s cohort makes the younger cohorts reduce their labor supply at the early stage, but increase their labor at later stages, which in turn makes the pseudo labor supply curve increase more in later calendar years relative to the actual one. Put differently, the same determinants that explain the decline of the actual labor supply since 2000 are also expected to explain the phenomenon of the more rapid increase of the actual (relative to the pseudo) labor supply from the mid-1980s until 2000. In subsequent discussions, I focus on the quantitative explanation of the change in aggregate labor supply from the 2000 to 2010 period. For reasons stated above, in the current model-based approach, I want to explain the decline in the actual labor supply relative to the increase in the pseudo labor supply. The relevant research question is, “Why did the actual labor supply go down for the 2000 to 2010 period, when it would have increased with no change from the older to the younger cohorts in the labor supply behavior?” Quantitatively speaking, the actual labor supply went down by 1.36 percentage points when the pseudo labor supply would have increased by 1.96 percentage points,

resulting in the pseudo reduction of 3.32 percentage points to be explained by between-cohort changes in the determinants and preferences. Finally, I identify major determinants whose changes explain the pseudo reduction of 3.32 percentage points.²⁸

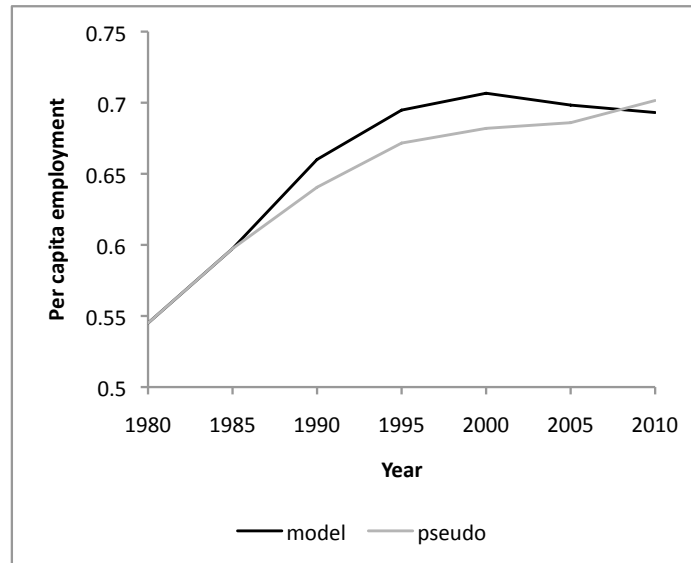


Figure 2.22: Aggregate Per Capita Employment Over Time (Model vs. Pseudo)

2.7.2 Contribution of Each Determinant

Changes in the opportunity cost of childbearing

Figure 2.24a shows how changes in the opportunity cost of childbearing explain the deviation of the actual labor supply from the pseudo one. Another hypothetical aggregate labor supply curve (represented by the dotted line) is derived and contrasted with the actual and pseudo labor supply curves, under the assumption that values of all the other determinants and preference parameters of the younger cohorts except for the opportunity cost are the same as those of the 1950s cohort. The increased opportunity cost from the older to the younger cohorts explains most of the deviation, as the dotted line and the dark solid line

²⁸ Changes in population shares of cohorts do not play a role in explaining the pseudo change in aggregate labor supply, as the same population shares are used to construct both the actual and the pseudo labor supply at each point in time. In addition, the CPS data show that changes in population shares alone would increase the actual labor supply even after 2000.

are very close to each other. With changes only in the opportunity cost of childbearing, the aggregate labor supply would drop by 0.26 percentage points from 2000 to 2010. Together with the increase in the pseudo labor supply for the same period (1.96), this results in 2.22 ($= 0.26+1.96$) percentage points of the pseudo reduction generated only by the increased opportunity cost of childbearing, which corresponds to 66.8 percent of the total pseudo reduction to be explained (3.32 percentage points). Just as changes in the opportunity cost play the dominant role in explaining the behavioral changes between the older and the younger cohorts, the same factor explains a major portion of the recent decline in the aggregate labor supply. Again, due to the increased opportunity cost of childbearing, the younger cohorts increase their labor supply (especially as full-timers) at the early stage of the life-cycle and delay childbearing relative to the older cohorts, which explains the rapid increase in the actual labor supply during the mid-1980s to the late 1990s. Upon childbearing, proportionally more of the younger cohorts tend to stay out of the labor force (from the mid-thirties) rather than choose part-time jobs, compared with the older cohorts, because of the relatively lower return to part-time experience and the greater rate of human capital depreciation for the younger than for the older cohorts. That explains the recent decline.

Changes in tax rates

Figure 2.24b deals with the effects of changes in the income tax rate associated with the children-related tax credits on aggregate labor supply. It is found that changes in this factor explain 11.1 percent of the total pseudo reduction. On the contrary, changes in the income tax rate that results from other sources (general income tax, capital gains tax, and payroll tax) negatively explains 23.2 percent of the total pseudo reduction, as shown in Figure 2.24c. Put together, changes in the overall tax code negatively explain 11.1 percent of the total pseudo reduction, which is revealed in Figure 2.24d.

Changes in business cycle conditions

Changes in business cycle conditions contribute to 20.1 percent of the total pseudo-reduction of aggregate labor supply (Figure 2.24e).

Changes in child care costs

As appeared in Figure 2.24f, changes in child care costs play an almost negligible role (3.8 percent) in explaining the total pseudo-reduction.

Changes in preferences

Figure 2.24g does a similar exercise with changes in preferences. Between-cohort differences in parameters of the utility function, especially between the 1950s and the 1970s, explain some of the total pseudo reduction of 3.32 percentage points, as the increase along the dotted line (1.32 percentage points between 2000 and 2010) is smaller than the increase along the pseudo labor supply curve (1.96). For the same period, the gap between the change in the pseudo labor supply and that in the hypothetical labor supply is 0.65, which corresponds to 18.9 percent of the total pseudo reduction.

2.7.3 Contributions of a Combination of the Determinants

Figure 2.25a provides the effects of a combination of changes in the opportunity cost and changes in the children related tax credits on aggregate labor supply. With the combined effect, the aggregate labor supply of married women would decrease by 1.01 percentage points between 2000 and 2010. Relative to the 1.96 percentage point increase in the pseudo labor supply, this results in a pseudo-reduction of 2.97 percentage points, which accounts for 89.5 percent of the total pseudo-reduction to be explained. When changes in business cycle conditions are additionally considered in Figure 2.25b, the combined effect of the three factors explains 106.1 percent of the total pseudo-reduction. Little change is made in the results when changes in child care costs are added in the analysis, as the addition explains 108.4 percent of the total pseudo-reduction (Figure 2.25c). Additional consideration of changes in tax rates coming from other sources than the children-related tax credits negatively explains changes in aggregate labor supply, with the combined effects of the five factors accounting for 83.4 percent of the total pseudo-reduction (Figure 2.25d). Lastly, adding changes in preferences in the analysis makes the dotted line overlap the actual labor supply curve perfectly, suggesting that the remaining 16.6 percent of the total pseudo-reduction is explained by changes in preferences.

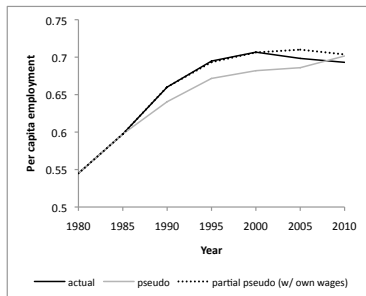
2.8 Conclusion

This study investigates the effects of changes in various determinants of labor supply on between-cohort changes in life-cycle labor supply behavior and ultimately provides a model-based quantitative explanation of the recent decline in the aggregate labor supply of married women. It documents that there have been important changes in the life-cycle labor supply behavior from the older to the more recent cohorts. While life-cycle labor supply functions are non-overlapping and bell-shaped for the older cohorts, they are roughly flat for the younger cohorts, and from the mid-thirties of the life-cycle, the younger cohorts continue to supply less labor than the older (1950s) cohort does.

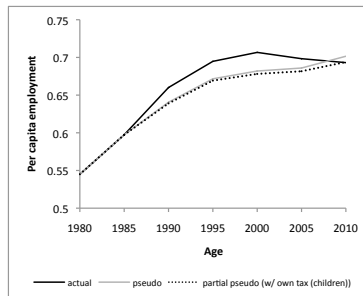
In a life-cycle model of women's labor supply, the behavioral changes are explained by the combination of changes in the opportunity costs of childbearing (as represented by returns to full-time and part-time experiences and the speed of human capital depreciation during a nonworking period), the children-related tax credits, business cycle conditions, and preferences, with the opportunity cost of childbearing being the dominant contributor. In particular, the increase in the opportunity cost represented by increased returns to full-time experience and the higher rate of human capital depreciation during a nonworking period makes the younger cohorts supply more labor relative to the older cohorts (especially in the full-time sector) at the early stage of the life-cycle and delay childbearing. Due to relatively low returns to part-time experience, the younger cohorts tend to choose the non-market sector rather than the part-time sector upon childbearing, and once the younger cohorts choose the non-market sector, the probability of returning to the paid-market becomes lower for the younger cohorts due to the higher rate of human capital depreciation, other things being constant.

A calibration of the model demonstrates that the aggregate labor supply of married women would increase by 1.96 percentage points from 2000 to 2010 if there were no changes between the older and the younger cohorts in the labor supply determinants and preferences; however changing the determinants and preferences for the same period actually results in a reduction of aggregate labor supply by 1.36 percentage points. Of the 3.32 percentage points of the pseudo-reduction of aggregate labor supply (difference between

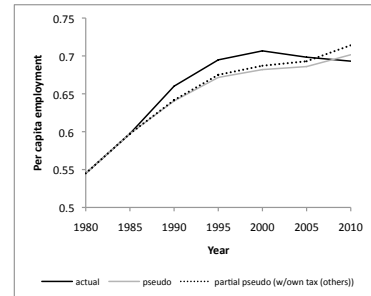
the hypothetical 1.96 percentage point increase and the actual 1.36 percentage point reduction), 66.8 percent is explained by the increased opportunity cost for the younger cohorts, and the rest is accounted for by a combination of reduction in the average tax rate associated with the increased children-related tax deduction, changes in business cycle conditions, and changes in preferences, among others.



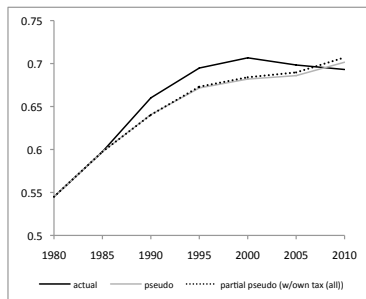
(a) Effects of Changes in Opportunity Cost of Childbearing



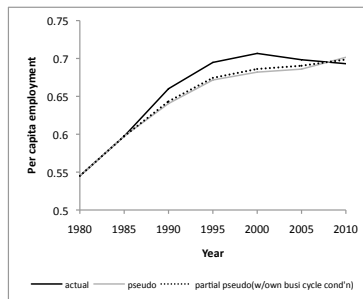
(b) Effects of Changes in Tax (Children)



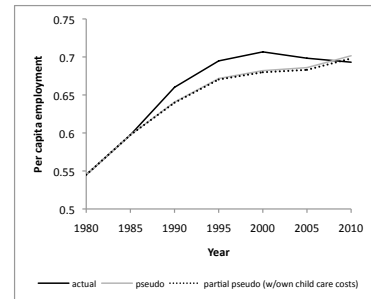
(c) Effects of Changes in Tax (Others)



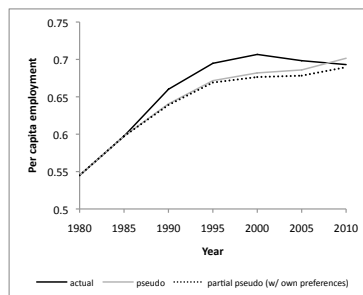
(d) Effects of Changes in Tax (all)



(e) Effects of Changes in Business Cycle Conditions

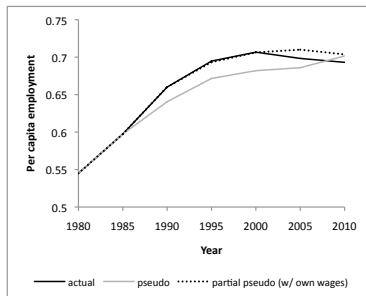


(f) Effects of Changes in Child Care Costs

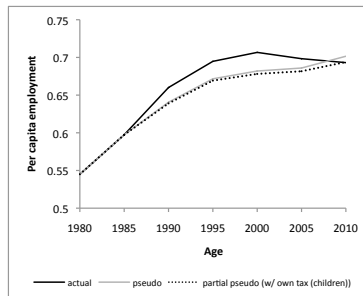


(g) Effects of Changes in Preferences

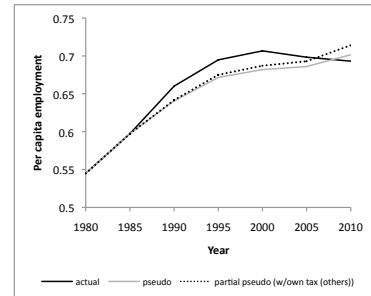
Figure 2.23: Effects of Changes in Each Determinants



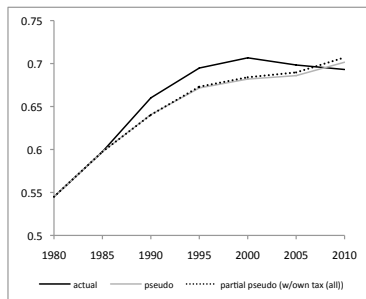
(a) Effects of Changes in Opportunity Cost of Childbearing



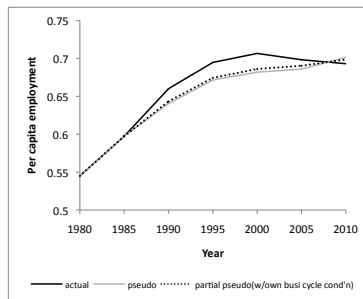
(b) Effects of Changes in Tax (Children)



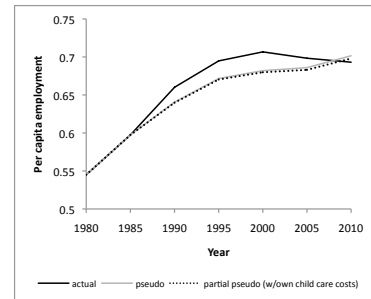
(c) Effects of Changes in Tax (Others)



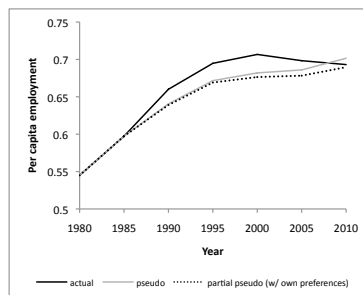
(d) Effects of Changes in Tax (all)



(e) Effects of Changes in Business Cycle Conditions

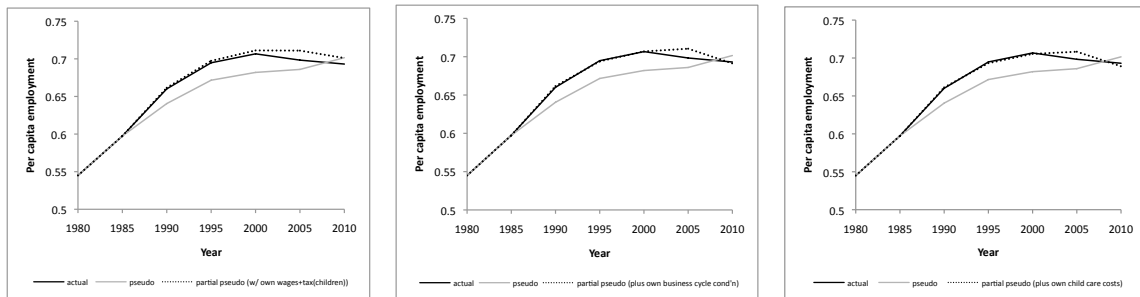


(f) Effects of Changes in Child Care Costs



(g) Effects of Changes in Preferences

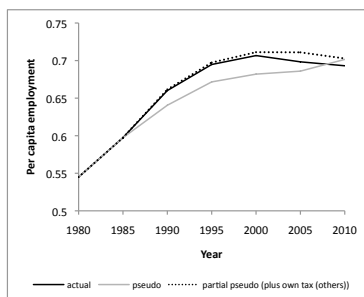
Figure 2.24: Effects of Changes in Each Determinants



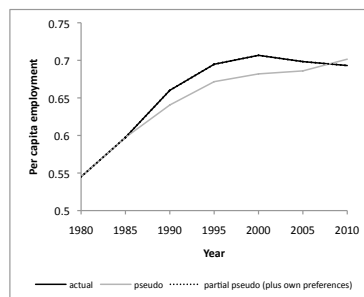
(a) Combination of Opportunity Cost of Childbearing and Tax (Children)

(b) Fig. 2.25a plus Business Cycle Conditions

(c) Fig. 2.25b plus Child Care Costs



(d) Fig. 2.25c plus Tax (Others)



(e) Fig. 2.25d plus Preferences

Figure 2.25: Combined Effects of Changes in Various Determinants

Chapter 3

Essay Two: Returning to School for Higher Returns

3.1 Introduction

As well recognized by many researchers, the marginal rate of private return (henceforth return) to education is an important determinant of an individual's education attainment and earnings. Repeated efforts have been made to identify the causal effect of education on earnings, with an emphasis on the potential bias associated with Ordinary Least Squares (OLS) estimates that may be subject to ability bias, attenuation inconsistency due to measurement errors in education, and/or, discount-rate bias (Lang, 1993; Card, 1995).¹ It is not the purpose of this paper to survey these issues, nor do I attempt to participate in any of these discussions with new evidence. Instead, this paper asks what type of information on the return to schooling is more helpful for individuals making decisions on their optimal levels of schooling. Does the return increase with years of investment? Or, is it diminishing with years of education? Or, is the return independent of the educational level, as is conventionally assumed in the vast majority of the literature on the education-earnings

¹ See Harmon and Walker (1995) for a review of various methods of dealing with endogeneity of schooling, Card (1999) for a complete survey of the literature on the causal effect of education on earnings along with a summary of the issues related with these three types of biases, and Harmon et al. (2003) for an updated and comprehensive survey of various microeconomics and econometrics issues on the returns to education.

relationship? More importantly, for a marginal decision maker who tries to determine whether or not to pursue an additional year of schooling by comparing the marginal rate of return with the marginal discount rate, how much return can he/she expect at each level of education?

These questions are best answered when I analyze cohort data rather than cross-sectional data. As well explained by Heckman et al. (2003), estimates of the return to different schooling levels based on cross-sectional data may not be representative of the rate of return that governs individuals' decisions on human capital investment, especially when skill prices change during a period of economic transition or when the quality of schooling changes across different cohorts. For example, as the relative price of college graduates increases permanently, a cohort of individuals who invest in college education just prior to the increase will enjoy higher returns to college investment than earlier cohorts do. Cross-sectional comparison, however, of college graduates and high school at a point in time would understate the true return to college (for a cohort of individuals who anticipate the rise in the skill premium), as the sample also includes earlier cohorts whose skill premium was relatively low. A similar argument can be made when school quality changes.²

On the basis of those respondents in the National Longitudinal Survey of Youth cohort (NLSY) who return to school after a certain period of job experience and take another job after completion of reinvestment in education, I investigate nonlinearity in the return to education. To the best of my knowledge, this paper is the first cohort-based longitudinal study that deals with the nonlinearity issue. To be specific, first I test whether the ability-free return becomes higher, lower, or remains the same at the higher level of education after reinvestment, relative to the lower level prior to reinvestment. The test for nonlinearity is conducted in a very flexible way without imposing any restrictive form on the return function. Rejecting the linearity assumption, I estimate a schedule of the ability-free marginal rate of return individuals can expect as they increase their education level over the course of the life-cycle. I also check robustness in the results by allowing different specifications, by controlling for the 'Ashenfelter's dip' that may be present in my

² Using the 1964-2000 Current Population Survey (CPS) March Supplements, Heckman et al. (2003, Figure 7a) find that the cohort-specific return to college tends to be higher than the return obtained from a cross-section of workers since the late 1970s.

sample of education changers, and by correcting for sample selectivity that may arise from using only those who actually decide to return to school.

Major findings are as follows. First, like many existing studies including Angrist and Newey (1991), my ability-free estimate is somewhat larger than the OLS counterpart. Second, the conventional assumption of linearity of log wages in years of schooling is strongly rejected in my cohort sample: a typical reinvestment in schooling for the 1980 through 1993 period (with the former education level being 13.4 years and the amount of reinvestment being 1.4 years) is associated with a rise of about 3.5 percentage points in the estimated return to an additional year of schooling. The change is also statistically significant. Third, the estimated return generally rises in the former education level, and reaches the maximum at 15 years of the former level (therefore 16 years of education after reinvestment), where an additional year of investment is associated with a rise in real hourly rate of pay by approximately 20 percent.³ Fourth, while the level of individuals' risk tolerance affects significantly the probability of returning to school, correcting for sample selectivity makes little difference in the results. Fifth, findings in the current paper survive a variety of additional robustness tests. The results are preserved even when sheepskin effects, year effects, and effects of the 'Ashenfelter's dip', among others, are controlled for. The current cohort-based evidence of the marginal return schedule, free of ability effects, is more helpful than existing evidence from cross-sectional data to individuals making schooling decisions.

The remainder of this paper is organized as follows. Section 3.2 provides a brief summary of existing studies in relation to the nonlinearity issue. Section 3.3 introduces my sample and related data issues along with an estimation strategy. Empirical findings are reported in Section 3.4. Section 3.5 concludes the paper.

3.2 A Review

It is a well-known fact that, in cross-sectional data, log earnings are approximately linearly related with schooling. For example, Card (1995) writes,

³ Although estimated returns are somewhat reduced beyond that point, I find the increasing portion of the return function more interesting, as a majority of the population completes up to 16 years of education. My estimates based on the Current Population Survey data reveal that the population proportion of those who completed 16 or fewer years of schooling is about 92.0%, 91.0%, 90.2% and 92.2% in 1980, 1985, 1990, and 1995, respectively. This is approximately my sample period.

“The approximate linearity of the cross-sectional relation between log earnings and schooling is an important stylized fact.”

Heckman and Polacheck (1974), Card and Krueger (1992), and Park (1994) all present supporting evidence of this fact. Consequently, in the literature of the schooling returns, the linearity assumption has been maintained in most studies, and relatively little attention has been paid to relaxing the linearity assumption.

Some studies address the nonlinearity issue based also on cross-sectional data. For example, on the basis of cross-country evidence, Psacharopoulos (1985, 1994) finds diminishing return to education investment with returns being the highest for primary education. Using repeated cross-sectional data from the UK General Household Survey for the 1974-1994 period, Harmon and Walker (1999) report that the marginal returns to schooling beyond age 18 is significantly lower than the marginal returns to schooling up to that age. Using the British National Child Development Survey, which surveyed all individuals born in Britain between 3 and 9 March 1958 at five different points, Blundell et al. (2000) compare hourly wages (at age 33 observed in the fifth wave) of individuals with Higher Education (HE) qualifications with those who had the prospect of undertaking HE but chose not to. It is found that estimated return to an undergraduate degree is about 17% for men and 37% for women, and that the returns to higher degrees courses are slightly lower than those to undergraduate degrees, but still statistically significant. Using also cross-sectional individual data for 12 countries received from the International Social Survey Programme, Trostel (2002, 2005) finds that the marginal rate of return is essentially nil for the first several years of schooling, it then increases rapidly until about year 12, and then it declines. A recent study by Song et al. (2008) focuses on estimated returns to post-graduate education. Using data from the 1993 National Survey of College Graduates, they find that, with nonrandom sorting into graduate school corrected for, estimated returns to graduate levels are not lower than those to a bachelor’s degree. Another strand of research by Hungerford and Solon (1987), Belman, and Heywood (1991), and Jaeger and Page (1996) also use cross-sectional data to present evidence of nonlinearity in the return that arises from sheepskin effects, where nonlinearity in the return depends on particular

levels of education, not the level of education in general. To summarize, although these cross-sectional studies provide supporting evidence of nonlinearity, they differ in the shape or the peak point of the return function.⁴

However, as well demonstrated by Card (1999) and many other studies cited therein, OLS estimates of returns to schooling based on cross-sectional data are generally subject to various types of biases: ability bias, attenuation inconsistency due to measurement errors in education, and/or, discount-rate bias. By the same token, with a few exceptions,⁵ existing studies dealing with the nonlinearity issue (aforementioned) are not free of these issues either, as their OLS estimates are also based on cross-sectional data. In an effort to estimate sheepskin effects in the return, Hungerford and Solon (1987) also mention that their estimates may be biased by omission of ability or other factors correlated with their education variable. Although they conjecture that omission of these factors may not distort their results, it is an empirical matter.

More importantly, as emphasized by Heckman et al. (2003), the rate of return to schooling estimated from cross-sections of workers often differs from the true rate of return faced by cohorts making their schooling decisions. This is particularly so, when skill prices or cohort quality changes.⁶ Using data from 1964-2000 March CPS data, they find that estimated returns from a cross-section of workers are not only biased in levels, but time patterns suggested by these estimates are often inconsistent with those obtained using a cohort-based estimation strategy.⁷ In addition, patterns of high school completion and college attendance decisions over their sample period are generally found to be consistent with cohort-based estimates of the return to high school and college for the same period.

⁴ Psacharopoulos (1985, 1994) shows significant diminishing returns with returns being the highest for primary education, Trostel (2002, 2005) reports that returns reach the maximum at around 12 years of education, Blundell et al. (2000) find that returns are higher at the first degree (undergraduate level) compared with lower school or higher degree levels, and Hungerford and Solon (1987) find that estimated returns are generally large and significant at diploma years with the maximum being reached at completion of 16 years. Finally, contrary to Blundell et al. (2000) and Hungerford and Solon (1987), Song et al. (2008) find that estimated returns are not lower at the post-graduate level than at the undergraduate level.

⁵ Harmon and Walker (1999) use various instruments to find that the results of nonlinearity are sensitive to the instruments used. Blundell et al. (2000) use individuals' math and reading ability test scores at age seven as proxy variables for their innate ability.

⁶ Citing Park's (1994) work, Card (1995) also observes that the slope of the log earnings-education relation varies from year to year in the Current Population Survey data.

⁷ Heckman et al. (1995) also test and reject the conventional assumption of linearity of the earnings-schooling relationship.

To fill the gap in the existing literature, I adopt data generated by cohort experience to test formally for nonlinearity in the return. Two features, among others, set the current study apart from existing cross-sectional studies that deal with the nonlinearity issue. First, I use longitudinal information on education investment and corresponding wage changes individuals actually experienced over the course of their work careers, and provide direct evidence on returns to education a cohort of individuals can expect at each level of education. Second, in my longitudinal framework, an individual's innate ability is directly controlled for by focusing on wage changes, and I use the longitudinal nature of the NLSY data to make reported education levels internally consistent and thereby reduce measurement errors in reported education years.

3.3 Data and Econometric Method

3.3.1 Data Issues

Following Angrist and Newey (1991), I use the National Longitudinal Survey of Youth (NLSY) random subsample to control for unobserved individual fixed-effects. Because initial educational investment and reinvestment behaviors are concentrated on the early stage of a work career, young workers in the NLSY sample are believed to provide me with abundant observations of education change. This survey began in 1979 with a national sample of young individuals aged between 14 and 22, reinterviewed the sample each year until 1994, and then switched to biennial interviews. My sample is drawn from 1979 through 1994 surveys, as, with the switch to biennial surveys, it is not entirely possible to pinpoint the timing of educational completion beyond 1994.⁸ Like Angrist and Newey (1991), I do not use the poverty sample nor the military sample, and use the hourly rate of pay on the main job as the dependent variable.

However, in addition to different study foci between Angrist and Newey and the current study,⁹ there are several important distinctions between my sample and Angrist and

⁸ This is the case when the difference in the education level (reported as of May in each survey) is one year between two adjacent biennial surveys.

⁹ The main purpose of Angrist and Newey (1991) is to test whether the fixed-effects assumption is appropriate in estimating human capital earnings function. In the process, they report that fixed-effects estimates of the return to schooling in the NLSY are roughly twice as large as OLS estimates.

Newey's in the characteristics of the final regression sample. First, by restricting their sample to those who were continuously employed from 1983 through 1987 and, at the same time, were still in school for at least part of their sample period, Angrist and Newey analyze wages from part-time or dead-end jobs that do not reward the kinds of skills and attributes that affect completed schooling and post-graduate earnings. This is the point made by Card (1995). On the contrary, wages in the current sample are restricted to those jobs obtained after completion of schooling. Second, respondents in Angrist and Newey's sample were not fully investing in education by simultaneously attending school and taking jobs. On the contrary, my sample is restricted to those who attend school without taking a job. By focusing on those who invest in education without a job and do jobs without investment, my analysis is an endeavor to capture full returns to full investment in education.¹⁰ Finally, I include women in my sample and test whether there exist gender differences in the return.

As noted by Griliches (1979) and Card (1999), among others, survey reports of the education variable are often subject to measurement errors. It is well recognized by researchers that measurement errors in reported education tend to attenuate estimated returns to education by a greater extent when I match wage changes with changes in education using longitudinal data. To reduce measurement errors in education, I use the longitudinal nature of the NLSY data to make reported education levels internally consistent. First, I restrict my sample only to the cases when the reported years of completed education (as of May) between two adjacent survey years remain the same or increase by one year. Second, as a way of pinpointing the timing of education changes, my sample requires that education levels remain the same for at least two consecutive years both right before the beginning and right after the end of education change. As an example, if a person reports completed education as 12, 12, 12, 13 and 14 only for five consecutive survey years, the case is discarded, even though numbers are internally consistent, as it is not clear whether the person completed her/his education in the last survey year.

Using a sample of only those who actually change education may produce biased results, when the choice of returning to school is not exogenously made. For example, estimated return based on a sample of actual education changers tends to overstate the true return,

¹⁰ Naturally my sample includes only employer changers, while Angrist and Newey's sample includes both employer stayers and employer-to-employer changers.

if the probability of returning to school is greater for those who expect greater return to an additional year of education than for otherwise comparable individuals who do not return to school. I consider this sample selectivity using a standard Heckman (1979) type two-step estimation method, where heterogeneity in individuals' risk preference is used to identify the selection effect. A meaningful identification, however, requires that individual's risk attitudes do not affect their wage changes, conditional on years of education reinvestment. The usage of individuals' risk preference as an excluded instrumental variable for their educational attainment is motivated by Brunello (2002), who sets up a simple static model to show that risk aversion affects in a natural way educational choice by influencing the marginal utility of schooling. In fact, while researchers have typically used school reforms, family backgrounds, and smoking as instruments for schooling, as noted by Brunello (2002), little attention has been paid to risk aversion as an instrument for attained education probably due to difficulty of measuring risk aversion in survey data. Using the Italian Survey on Household Income and Wealth data, Brunello measures the Arrow-Pratt index of absolute risk aversion for each individual and shows that measured risk aversion can be safely excluded from the Mincerian earnings function. Unlike Brunello, however, I use individuals' risk attitudes at the time of reinvestment, not current, which allows me to effectively control for time-varying as well as time-invariant components of individuals' risk attitudes. The Appendix provides a brief discussion of how individuals' attitudes toward risk satisfy an exclusion restriction in my NLSY sample. Finally, in the empirical execution, I borrow Light and Ahn's (2010) measure of risk tolerance computed for each respondent in the same NLSY sample that is adopted in the current study. During three out of twenty-two interviews conducted from 1979 through 2004, respondents were asked whether they would accept two hypothetical, lifetime income gambles of varying riskiness. Light and Ahn used multiple responses to these questions to estimate an Arrow-Pratt index of relative risk tolerance that accounts for both measurement error and aging effects.¹¹

¹¹ The data were generously supplied by the authors.

3.3.2 Econometric Model

I begin with a standard Mincer (1974) wage function in estimating the returns to education:

$$\ln W_{it} = \theta_1 + \theta_2 \text{Age}_{it} + \theta_3 \text{Age}_{it}^2 + \gamma \text{Education}_{it} + \delta' X_{it} + \mu' X_i + \epsilon_{it} \quad (3.1)$$

where $\ln W_{it}$ is real hourly rate of pay on the main job held by individual i during the survey week in year t , deflated by the Consumer Price Index (CPI) of that year, Age represents the person's age, Education_{it} is years of education completed as of year t , X_{it} and X_i are time-varying and time-invariant characteristics, respectively, and ϵ_{it} is the error term. Also, γ represents the return to an additional year of schooling for someone whose education level is Education_{it} . Equation (3.1) shares the common specification adopted by many existing studies, such as Ashenfelter and Krueger (1994) and Angrist and Krueger (1991), that estimate pure returns to schooling.

Following Angrist and Newey (1991), the error term is composed as follows.

$$\epsilon_{it} = \alpha_i + u_{it} \quad (3.2)$$

where α_i represents innate ability of individual i which is probably correlated with the education level, and the individual-and-time specific error term, u_{it} , is at a minimum assumed to be independent of regressors.

One easy way of controlling for α_i as well as X_i , and therefore estimating γ consistently, is to use the sample of education changers, observe wages received from the job taken after reinvestment in education, and explain the wage growth rate between the two points by corresponding years of education change. In my empirical implementation, year t is the last year wages are observed from the previous job, and year $(t + s)$ is the first year wages are observed from the reemployed job. Subtracting equation (3.1) from the equation observed at time $t + s$ yields

$$\begin{aligned}
\ln \frac{W_{i,t+s}}{W_{it}} &= \theta_2 s_i + \theta_3 [2(s_i \times Age_{it}) + \gamma_3 s_i^2] \\
&+ \gamma (Education_{i,t+s} - Education_{it}) + \delta' (X_{i,t+s} - X_{it}) + (u_{i,t+s} - u_{it}) \quad (3.3) \\
&= \beta' Z + \gamma (Education_{i,t+s} - Education_{it}) + \Delta u
\end{aligned}$$

where $\beta' Z = \theta_2 s_i + \theta_3 [2(s_i \times Age_{it}) + \gamma_3 s_i^2] + \delta' (X_{i,t+s} - X_{it})$, and $\Delta u = u_{i,t+s} - u_{it}$.¹² In equation (3.3), all individual-specific but time-invariant characteristics, observable or not, are differenced out.

Ordinary Least Squares (OLS) estimation of equation (3.3) would still produce inconsistent estimates of γ , if education changes are not randomly determined. To be specific, if changers and non-changers are systematically different in some attributes that are correlated with the error term in equation (3.3), estimation of equation (3.3) by OLS may be subject to omitted variable bias. Suppose decision of education change is affected primarily by the person's attitude toward risk:

$$Education_{i,t+s} - Education_{it} = \lambda_0 + \lambda_1 R_{it} + \nu_{it} \quad (3.4)$$

where R_{it} represents the extent of risk tolerance individual i has at the time of making a decision of whether or not to return to school, year t . Then, conditional on education change,

$$\begin{aligned}
&E \left(\ln \frac{W_{i,t+s}}{W_{it}} | Education_{i,t+s} - Education_{it} > 0 \right) \\
&= \beta' Z + \gamma (Education_{i,t+s} - Education_{it}) + E[\Delta u | \nu_{it} > -(\lambda_0 + \lambda_1 R_{it})] \quad (3.5) \\
&= \beta' X + \gamma (Education_{i,t+s} - Education_{it}) + IMR(R_{it})
\end{aligned}$$

¹² To be precise, i represents case instead of person, as some individuals experience more than one education change. See summary statistics in Table 3.1. All the empirical findings in the current paper are preserved even when the sample is restricted to those who experience only one education change. The results are electronically available upon request.

where $IMR(R_{it}) = \rho_{\Delta u, \nu} \sigma_{\Delta u} \frac{\phi(\lambda_0 + \lambda_1 R_{it})}{\Phi(\lambda_0 + \lambda_1 R_{it})}$, where $\rho_{\Delta u, \nu}$ represents the correlation of the two error terms in equation (3.3) and (3.4), $\sigma_{\Delta u}$ is the standard deviation of the error term in equation (3.3), and $\phi(\cdot)$ and $\Phi(\cdot)$ are a density and a cumulative distribution function of a standardized normal random variable, respectively. If education changers tend to enjoy higher wage growth than otherwise comparable non-changers ($\rho_{\Delta u, \nu} > 0$), estimated return from equation (3.3) is subject to omitted variable bias.

Specification of equation (3.5) is restrictive in the sense that the return to an additional year of education is the same as γ regardless of the education level already accumulated. To allow the rate of return to vary with the education level, I construct an unrestricted model:

$$\begin{aligned} E \left(\ln \frac{W_{i,t+s}}{W_{it}} \right) \\ = \beta' Z + (\gamma^{t+s} - \gamma^t) Education_{i,t+s} + \gamma^t (Education_{i,t+s} - Education_{it}) + IMR(R_{it}) \end{aligned} \quad (3.6)$$

$$= \beta' Z + (\gamma^{t+s} - \gamma^t) Education_{i,t} + \gamma^{t+s} (Education_{i,t+s} - Education_{it}) + IMR(R_{it}) \quad (3.7)$$

where γ^t and γ^{t+s} represent the marginal returns at the education levels before and after reinvestment, respectively. Equations (3.6) and (3.7) are identical except for the time index used: in equation (3.6), the educational level and the coefficient of the education change are indexed at $(t+s)$ and t , respectively, while equation (3.7) uses opposite time indices. In both equations, significance of the coefficient of the educational level implies non-linearity in the returns to schooling with a positive and negative number showing increasing and decreasing returns to education, respectively. Equations (3.6) and (3.7) are flexible in the sense that no specific form is specified for the return function. As such, my test results are robust to misspecification of the return function.

Lastly, for the purpose of estimating a more concrete schedule of the marginal rate of return, a set of dummy variables for the former education level are constructed, interacted with education change, and are included in the place of the education change variable in

equation (3.5). The coefficient of each interaction term represents the marginal return a potential investor would expect at each education level he/she already accumulated.

3.4 Empirical Findings

3.4.1 Sample Characteristics

Table 3.1 summarizes education “changes” experienced by individuals in my NLSY random subsample. With the poverty and the military sample excluded, there are originally 6,111 individuals aged 14 to 22 as of 1979. The entire annual surveys from 1979 through 1994 are used in the current analysis. With all the restrictions to reduce measurement errors in education, 1,142 individuals are identified to have changed their education levels at certain points in time. Due to the sample restriction that reported education levels be the same at least for two consecutive years right before and right after education change, the first education change observed in my sample period is 1980 and the last one ended in 1993. Among 1,142 respondents, approximately 16 percent experience education change more than one time. Figures in the second column are based on the sample which is used in my regression analysis. In addition to those who do not have valid observations on the variables used in the regression, those “on-the-job” education changers who change their educational level as an employee (Angrist and Newey’s sample) are also dropped from the final sample, which leaves me with 885 person-cases experienced by 767 individuals. However, relative frequency distributions remain very similar between the two columns.

Using the entire sample in the first column of Table 3.1, Figure 3.1 displays frequency of education change by the size of education change and by the former education level. Among the total number of case-person observations (1,344), 73 percent pertain to a one-year change in education, 17 percent to a two-year change, 7 percent to a three-year change, and 2 percent belong to a four-year change in education. The former education level before returning to school varies greatly with the 12th grade being the most frequently observed level. Returning to school to benefit from the “sheepskin effects” is also observed in the data. For example, although one-year upgrading is the most-frequently observed in most cells, comparison of within-cell relative frequencies across cells reveals that one-year, two-year, three-year, and four-year change appear the greatest as 93%, 42%, 13%, and 3%,

Table 3.1: Frequency of Educational Change for the 1980-1993 period

Number of Changes	Number of individuals (% of the total)	
	Original Sample	Regression Sample
1	958 (0.8389)	656 (0.8553)
2	169 (0.1480)	105 (0.1369)
3	13 (0.0114)	5 (0.0065)
4	2 (0.0018)	1 (0.0013)
Total	1,142	767

Source: National Longitudinal Survey of Youth for the 1980-93 period. Figures are based on the random subsample, excluding the poverty and the military sample.

when the former educational levels are 15, 14, 13, and 12 years, respectively.

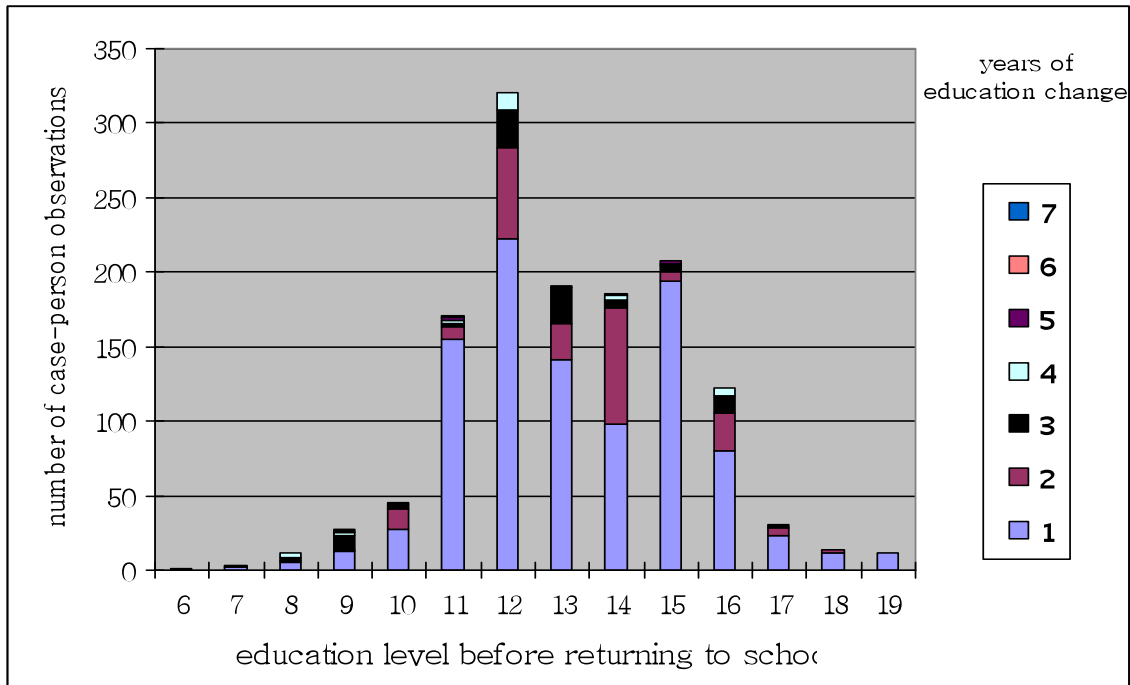
Although, for brevity, not reported in a separate table, the sample mean of s is 2.84 years, in comparison with 1.41 years of sample mean of education change. The difference between the two sample means is statistically significant. Standard deviations of s and education change are 2.12 and 0.82 years, respectively. Lastly, in my regression sample, the sample mean, standard deviation, the minimum, and the maximum value of risk tolerance are 0.89, 1.09, 0.12, and 9.02, respectively.

3.4.2 Estimated Returns to Education

Table 3.2 reports the estimated returns to education. The estimates in column 1 through 6 are obtained by my differencing method and, therefore, free of ability bias. F-tests cannot reject the null hypothesis of no gender difference in regression coefficients in either my basic model (column 1 through 3) or the model with additional control variables (column 4 through 6). My ability-free estimate in column 6 shows that an additional year of schooling leads to a rise in real hourly wage rate by 8.6 percent.¹³ This estimate is very similar to the ability-free estimates found in existing studies, in particular, to those in twin-based studies¹⁴ and the one obtained by Angrist and Newey (1991). The similarity between

¹³ Assuming that u_{it} 's are identically distributed, the variance of the differenced error becomes greater if $Cov(u_{i,t+s}, u_{it})$ decreases in S . In all cases, however, a χ^2 -test cannot reject the homoskedasticity hypothesis even at the ten percent significance level.

¹⁴ See Table 6 of Card (1999) for a good summary of these twin studies.



Source: National Longitudinal Survey of Youth for the 1980-93 period. The total number of case-person observations is 1,344, which corresponds to 1,142 workers who experience education changes at least once.

Figure 3.1: Size of Education Change by Education Level

the current study and Angrist and Newey (1991) is notable considering differences in the sample between the two studies: while I consider cases where individuals either take jobs or are in school, not both, respondents in Angrist and Newey's sample attend school as an employee.

Estimates in the last column are obtained by applying OLS to the level equation based on the very sample used in estimating the differenced equation. In this "balanced" sample, real hourly wages increase by 7.3 percent following an additional year of schooling, which is somewhat smaller than the ability-free estimate. This finding is quite consistent with recent estimates of the return to education, as well summarized in Card (1995). In particular, Angrist and Newey's results also show a higher return to education from the fixed-effects model than the corresponding OLS model, although the difference between the fixed-effects estimate and the OLS one is somewhat larger in Angrist and Newey than the current study.

Estimates in Table 3.2 may be subject to a selection bias by including in the sample only those who actually changed their education level. If the probability of returning to school is greater for those who expect greater returns to an additional year of education than for otherwise comparable individuals who do not come back to school, the estimated return based on actual education changers tend to overstate the true return. To check the potential selection bias associated with using the endogenously selected sample of education changers, Table 3.3 reports estimates based on equation (3.5). Column 1 imports my ability-free estimates in column 6 of Table 3.2, and the remaining columns show selectivity-corrected ability-free estimates. Looking at the estimated Probit equation in the last column, it is evident that a greater level of risk tolerance increases the probability of returning to school. In addition, the inverse Mills ratio enters significantly into all wage growth equations from column 2 through 6, implying that the probability of returning to school and the wage growth rate are positively correlated. Including the inverse Mills ratio in the wage growth equation, however, does not reduce estimated return significantly, as is evident in comparison of estimates between column 1 and 2. In column 3, I include a dummy variable for diploma years as additional regressor, which equals one if reinvestment of schooling ends up with 8, 12, or 16 years of education, and found that controlling for sheepskin effects reduces estimated return to education slightly. With year dummies added additionally (column 4), estimated return is reduced slightly to 7.1%. Estimated sheepskin effects are significant, whether or not year dummies are controlled for.

Estimated returns obtained by my differencing method may exaggerate true returns if wages at the timing of decision making (W_{it} in equation (3.5)) are already subject to the ‘Ashenfelter’s dip,’ which is an empirical regularity that the mean earnings of participants in employment and training programs generally decline during the period just prior to participation (Ashenfelter, 1978). My basic method of dealing with the ‘Ashenfelter’s dip’ is to use more lagged wages from the pre-investment job ($W_{i,t-l}$) and subtract them from post-investment wages ($W_{i,t+s}$) so that wage changes observed over a longer period are less affected by the ‘dip’ impact. Given that the sample size adopted in the current analysis is relatively small, I examine pre-investment wages lagged by one year ($l = 1$). I first restrict my sample to those who are in the same job and report wages for at least two consecutive years prior to reinvestment, which reduces the number of my differenced observations in my

full sample dramatically to 422. Then, using the 422 observations, I reestimate equation (3.5) with the most expanded specification in column 4 of Table 3.3, and report the results in column 5 of Table 3.3. Finally, using the same ‘balanced sample’, I redo the analysis with the dependent variable replaced by $\ln(W_{i,t+s}/W_{i,t-1})$, whose results are in column 6. In the balanced sample, estimated return is somewhat reduced from 10.1% to 8.0% by adopting longer differencing, supporting evidence for the ‘Ashenfelter’s dip’.¹⁵ As will be demonstrated in a subsequent section, however, my main results of nonlinearity in returns are quite robust to consideration of the ‘dip’.

¹⁵ Although not reported for brevity, I also try $l = 2$ with an even smaller sample, and find little evidence of the ‘Ashenfelter’s dip’ at $(t - 1)$, implying that the ‘dip’ impact is prominent just prior to the period of investment. This line of tests, however, generally suffers from a small sample problem.

3.4.3 Nonlinearity in the Returns to Schooling

Table 3.4 reports estimated equations (3.6) and (3.7), where the return to education is estimated in a more flexible way: the return is allowed to vary with the education level and no functional form is pre-specified about non-linearity of the return. Because the two equations produce identical results except for the coefficient of education change, I report the estimated coefficient of education change in equation (3.6) (γ^t) and that in equation (3.7) (γ^{t+s}) in the same column along with other estimated coefficients. Results show a strong evidence for increasing returns to education. For example, figures in column 3¹⁶ show that, all the other things being constant, the estimated return increases from 4.3% at the former education level to 8.6% at the higher education level after reinvestment. The difference (4.3 percentage points), the estimated coefficient of the education level, is statistically significant even at the 1% significance level. The difference remains significant even when I control additionally for sheepskin effects (column 4) and also for year effects (column 5). Column 6 uses the same specification as column 5 except that, in column 6, S is replaced by $S - \Delta Education$. This is the case where equation (3.1) is specified as a quadratic function of potential experience, not age. As the education level increases by $\Delta Education$, potential experience increases by $S - \Delta Education$ between t and $t + s$. This exercise, however, does not change any of my previous results. Last two columns test if the current results are robust with respect to consideration of the ‘Ashenfelter’s dip’. For the most expanded specification in column 5, I follow the same procedure as in columns 5 and 6 of Table 3.3. Results show that this exercise makes little change to the observed pattern of increasing returns. In fact, the estimated coefficient of education level becomes greater when I consider the ‘dip’ effects in column 8.

While estimates in Table 3.4 suggest that estimated returns increase as individuals invest more in education, the results are not entirely informative in the sense that they hold for a typical or an average case: a typical education changer whose former education level is 13.4 years invests about 1.4 years and enjoys an *additional* return to education of 3 to 4 percentage points from a post-reinvestment job. A potential investor in education would require a more complete return schedule, the size of expected return at each education

¹⁶ An F-test cannot reject the null hypothesis of no gender difference in regression coefficients at the 10% significance level ($F_{8,869} = 0.58$).

level. For that purpose, I create seven dummy variables for the former education level (less than or equal to 11, 12, 13, 14, 15, 16, and more than or equal to 17), interact them with education change, and include these seven interaction terms in the place of education change in equation (3.5). While, for brevity, estimated coefficients of other control variables are not reported, they are generally very similar to those in Table 3.4. The first three columns of estimates in Table 3.5 correspond to the three sets of estimates from column 3 to 5 in Table 3.4, and the last two columns examine effects of the ‘Ashenfelter’s dip’ on the current issue. Focusing on the third column where a full set of control variables are included, estimates confirm the existence of nonlinearity in the return. An F-test rejects a null hypothesis of inter-education group homogeneity in the marginal return at the 5 percent significance level ($F_{6,859} = 2.11$). And, estimated returns continue to rise until the former education level reaches 15 (so that an additional year of investment ends up with 16 years of education), where an additional year of schooling is associated with a rise in the real wage rate by about 20 percent. After that, the marginal return drops substantially and then rises again to the level of return at 14 years of former education. This pattern is preserved in all three columns.

Additional tests are conducted about robustness of the observed pattern of nonlinearity. First, controlling for effects of the ‘Ashenfelter’s dip’ does not change the observed pattern of nonlinearity, as is evident from the last two columns of Table 3.5. Increased standard error estimates that result from the reduced sample size make me barely accept the null hypothesis of inter-group homogeneity in the return at the 10 percent significance level ($F_{6,397} = 1.51$ in the last column).

Second, including group dummies for diploma years separately, one for 12 years and the other for 16 years in the regression equation makes little difference in the observed pattern of nonlinearity. With this new exercise, the seven estimated coefficients in my most preferred specification (the most expanded specification in the third column of Table 3.5) change to 0.0416, 0.0517, 0.0620, 0.1058, 0.1747, 0.0899, and 0.1672, respectively, with the last four coefficients estimated significantly. Due to relatively large standard error estimates, however, the null hypothesis of inter-group homogeneity in the return cannot be rejected even at the 10 percent level. A larger sample size would change the result. For example, when I omit the union dummy variable from the regression, the number

of differenced observations increases from 885 to 973 (due to missing values of the union variable), and, although not reported for brevity, all my previous findings are preserved in this new sample. In addition, this slightly increased sample makes me reject the null hypothesis of inter-group homogeneity in estimated returns at the 10% level, even though I allow different sheepskin effects for different diploma years ($F_{6,947} = 1.78$). It is also worth noting that estimated coefficient of the dummy for completion of 16 years is 0.136 with associated standard error estimate 0.060, supporting for existence of sheepskin effects.

Finally, I redo most of previous analyses using average hourly earnings, defined by the ratio of total annual labor income from all jobs to total annual hours, instead of the hourly rate of pay from the main job. I also try a sample of 656 individuals who experience education change only once. All the current findings are preserved even with these two exercises.

Estimates in Table 3.5 suggest that the general shape of the estimated return function appears similar between the current study and existing ones in the sense that estimated returns go up to a certain level of investment and then decline. However, aside from differences between cohort-based evidence and cross-sectional evidence, previously mentioned, and different peak points of the estimated return function, the current study also departs from existing ones by formally testing if observed nonlinearity is generated by sheepskin effects. Existing cross-sectional studies often estimate returns to different degrees, not to different years, which makes it difficult to identify if the observed nonlinearity is due to education or credentials at specific stages of education. As noted by Trostel (2002, 2005), similar difficulty is found in estimating returns as a smoothing function of years of education. Hungerford and Solon (1987) are most comparable to the current study in that they also estimate the return by an unrestricted step function. In fact, their large CPS sample, May 1978, enables them to estimate the step at each stage of education from one through eighteen years. Table 2 of their results show that, with an exception of thirteen years of investment (dropout at the first year of college), step-specific returns are large and significant only at diploma years. Unlike Hungerford and Solon, the current study finds that estimated returns increase up to 16 years even after sheepskin effects are controlled for.¹⁷

¹⁷ Although, unlike Hungerford and Solon, I find substantial returns even for dropouts, the current analysis does find evidence of sheepskin effects, which is different from Layard and Psacharopoulos (1974).

In Table 3.6, I conduct a very preliminary test of whether or not the observed nonlinearity is related with technological progress. In measuring technological change, I follow suggestions of Bartel and Sicherman (1999) to use the NBER total factor productivity growth series described in Bartelsman and Gray (1996) (henceforth *TFP*), the ratio of R&D funds to net sales reported by the National Science Foundation (*R&D RATIO*), and the ratio of scientific and engineering employment to total employment calculated from the 1979 and 1989 CPS by Allen (1996) (*SCIENTISTS RATIO*).¹⁸ I compute technological change between t and $t + s$ by the growth rate of total factor productivity between the two time points. For *R&D RATIO* and *SCIENTISTS RATIO*, I simply calculate the difference in the ratio between t and $t + s$. Then, in equations (3.6) or (3.7), I allow the coefficient of the education level, which reflects change in the return ($\gamma^t - \gamma^{t+s}$), to be a linear function of technological change observed for the same period of individual investment, which is equivalent to including in the equation an interaction of the education level and the technological change variable as an additional regressor. In the expanded equation, therefore, measures of technological change vary across individuals depending on starting and ending time points of education reinvestment. For brevity, Table 3.6 reports coefficients of only education-related variables. As the two equations produce virtually identical results regarding the coefficient of the education level, I report estimation results of equation (3.7) only. In this test, I use the full set of control variables, as appeared in the fifth column of Table 3.4. In this set-up, a coefficient of the education level implies change in the return that is not related with technological change, and a coefficient of the education level interacted with technological change means change in the return associated with technological change. Results show that, no matter what variables are used to represent technological change, the coefficient of the education level remains unchanged, as appeared in the estimate in the fifth column of Table 3.4. In all cases, the estimated coefficient of the interaction term enters the equation very insignificantly, and it appears even negative when *SCIENTIST RATIO* is used. This implies that the pattern of *increasing returns*

¹⁸ The first and the second variables are directly imported from the NBER productivity data base and the National Science Foundation, respectively. For the third technology variable, I follow Allen (1996) to compute the series using the Current Population Survey data for an expanded period from 1979 to 1994. While Bartel and Sicherman (1999) suggest three more technology variables in addition to the above three, they are not adopted by the current study, because those variables are not available at least for part of my sample period.

to investment observed in my cohort sample is not explained by concurrent technological change.¹⁹

¹⁹ When year dummies are excluded from the equation, estimated coefficient of the interaction term appears positive in all cases, and even significant at the 5 percent level when *TFP* is used to measure the level of technology. However, little change is made to estimated coefficients of the education level in Table 3.6, even with omission of year dummy variables.

Table 3.3: Selectivity-Corrected Ability-Free Estimates

<i>Variables</i>	OLS on wage change equation	Selectivity-corrected estimates					
		Wage change equation					Probit equation
		Full sample			Effects of the Ashenfelter's dip		
					$\ln \frac{W_{i,t+s}}{W_{i,t}}$	$\ln \frac{W_{i,t+s}}{W_{i,t-1}}$	
$\Delta Education$	0.0863*** (0.0278)	0.0842*** (0.0278)	0.0774*** (0.0276)	0.0706** (0.0281)	0.1008* (0.0493)	0.0803* (0.0488)	-
S	0.0674 (0.0473)	0.0780* (0.0476)	0.0661 (0.0473)	0.0249 (0.0520)	0.0755 (0.0934)	0.1440 (0.1019)	-
$2 \times Age_t$ $\times S + S^2$	-0.0013* (0.0008)	-0.0014* (0.0008)	-0.0012 (0.0008)	-0.0004 (0.0009)	-0.0009 (0.0016)	-0.0029 (0.0018)	-
$Tenure_t$	-0.0333** (0.0146)	-0.0339** (0.0146)	-0.0337** (0.0145)	-0.0315** (0.0148)	-0.0358** (0.0166)	-0.0213 (0.0203)	-
$\Delta Union$	0.1632*** (0.0502)	0.1636*** (0.0501)	0.1702*** (0.0498)	0.1645*** (0.0501)	0.1536** (0.0710)	0.1630** (0.0650)	-
IMR	- -	0.3326* (0.1894)	0.3784** (0.1883)	0.3664** (0.1896)	0.6818** (0.3155)	0.6538** (0.3121)	-
<i>Sheepskin Effect</i>	X	X	O	O	O	O	-
<i>YearDummies</i>	X	X	X	O	O	O	-
<i>Risk Tolerance</i>	-	-	-	-	-	-	0.1142*** (0.0171)
N	885	885	885	885	422	422	5,039
R^2	0.0366	0.0400	0.0560	0.0744	0.0699	0.0677	-
<i>Log Likelihood</i>	-	-	-	-	-	-	-2498.76

The sample includes both men and women. In column 1 through 6, the dependent variable is change in logarithm of the real hourly rate of pay between the last survey week point before education change and the first survey week point after. In the last column, the dependent variable is a dummy variable which equals one for education changers and zero for non-changers. Each equation also includes an intercept term. S represents time distance in years between the two survey week points, and a subscript of t represents the last survey week year before returning to school. IMR stands for inverse Mills ratio. $RiskTolerance$ is represented by estimated Arrow-Pratt index of relative risk tolerance, supplied by Light and Ahn (2010). *Sheepskin Effect* is a dummy variable which equals one if the education level is 8, 12, or 12 years after education change. Numbers in parentheses stand for estimated standard errors. *, **, and *** = significant at the 10%, 5%, and 1% level, respectively.

Table 3.4: Testing for Nonlinearity in Returns to Education

Variables	Full sample						Effects of the Ashenfelter's dip	
	Men	Women	All	All	All	All	$\ln \frac{W_{i,t+s}}{W_{i,t}}$	$\ln \frac{W_{i,t+s}}{W_{i,t-1}}$
<i>Education Level</i>	0.0542*** (0.0177)	0.0314* (0.0167)	0.0429*** (0.0121)	0.0351*** (0.0123)	0.0347*** (0.0126)	0.0339*** (0.0124)	0.0390*** (0.0175)	0.0534*** (0.0172)
$\Delta Education$ <i>Equation (3.6)</i>	0.0242 (0.0429)	0.0608 (0.0418)	0.0432 (0.0299)	0.0448 (0.0298)	0.0397 (0.0301)	0.0504* (0.0279)	0.0679 (0.0512)	0.0343 (0.0505)
$\Delta Education$ <i>Equation (3.7)</i>	0.0784** (0.0387)	0.0922** (0.0397)	0.0861*** (0.0276)	0.0799*** (0.0275)	0.0744*** (0.0280)	0.0843*** (0.0269)	0.1068** (0.0491)	0.0877* (0.0483)
<i>S</i>	0.1451* (0.0752)	0.1085* (0.0650)	0.1282*** (0.0494)	0.1089** (0.0495)	0.0634 (0.0537)	0.0785 (0.0593)	0.1158 (0.0946)	0.1959* (0.1022)
$2 \times Age_i \times S + S^2$	-0.0026** (0.0012)	-0.0018* (0.0010)	-0.0022*** (0.0008)	-0.0018** (0.0008)	-0.0010 (0.0010)	-0.0013 (0.0010)	-0.0015 (0.0016)	-0.0036** (0.0018)
<i>Tenure₋₁</i>	-0.0376* (0.0225)	-0.0375** (0.0188)	-0.0370*** (0.0145)	-0.0363** (0.0496)	-0.0336** (0.0147)	-0.0337** (0.0147)	-0.0359** (0.0166)	-0.0178 (0.0201)
$\Delta Union$	0.1125 (0.0724)	0.2275*** (0.0683)	0.1658*** (0.0498)	0.1710*** (0.0496)	0.1647*** (0.0499)	0.1645*** (0.0499)	0.1576** (0.0706)	0.1729*** (0.0644)
<i>IMR</i>	0.4231* (0.2299)	0.3863 (0.4841)	0.3463* (0.1882)	0.3829** (0.1876)	0.3722** (0.1089)	0.3722** (0.1887)	0.6665** (0.3141)	0.6262** (0.3089)
<i>Sheepskin Effect</i>	X	X	X	O	O	O	O	O
<i>Year Dummies</i>	X	X	X	X	O	O	O	O
<i>N</i>	461	424	885	885	885	885	422	422
<i>R²</i>	0.0502	0.0687	0.0536	0.0647	0.0825	0.0829	0.0789	0.0873

The dependent variable is change in logarithm of the real hourly rate of pay between the last survey week point before education change and the first survey week point after. Each equation also includes an intercept term. Coefficients of *Education Level* represent changes in returns to education, those of $\Delta Education$ in equation (3.6) represent returns to education after education change. Except for $\Delta Education$, coefficients of all the other variables are identical between the two equations. In column 6, *S* is replaced by $S - \Delta Education$. Numbers in parentheses stand for estimated standard errors. *, **, and *** = significant at the 10%, 5%, and 1% level, respectively.

3.5 Conclusion

This paper is the first cohort-based study that provides a relatively complete schedule of ability-free returns by the education level. On the basis of those respondents in the National Longitudinal Survey of Youth (NLSY) who return to school after a certain period of job experience, this paper finds strong evidence of increasing returns to investment: a typical reinvestment for the 1980 through 1993 period is associated with a rise of about 3.5 percentage points in the estimated return to an additional year of schooling. Estimated returns to an additional year of schooling continue to rise in the former education level, reach the maximum at 15 years of the former level (so that reinvestment ends up with 16 years of education), and decline beyond that point. Cohort-based estimates like current ones are helpful for individuals making schooling decisions.

The current results survive a variety of robustness tests. While the level of individuals' risk tolerance affects significantly the probability of returning to school, correcting for sample selectivity makes little difference in my results. The current findings also remain valid when I control for year effects, effects of the 'Ashenfelter's dip', and even for sheepskin effects. The observed pattern of increasing returns to education is not explained even by concurrent technological change. These observations suggest that an individual's life-cycle production is a convex function of education until she/he invests up to 16 years in education.

A number of important limitations need to be considered. The main weakness of this study is the small sample, which limits my analysis in several ways. Not only does it prevent me from reporting a full schedule of the marginal rate of return, but also it limits test power of various hypotheses and even hinders me from testing some hypothesis more effectively. For example, a larger sample would allow me to investigate the issue of the 'Ashenfelter's dip' more thoroughly, by examining more lagged wages. Another related issue is that the current study exploits information on education investment and wage outcome obtained from an early stage of work career. In my sample, respondents return to school at age 24 on average, and 35 at the oldest. To the extent on-the-job training has differential effects on wages before and after reinvestment, so that wage growth rates are affected by this factor, my estimates will be biased. Finally, it is also acknowledged that the proxy variables for technological change adopted in the current study is far from

ideal. In my wage change equation, they vary across individuals depending on when they increase their education attainment and how long they invest. Ability of the measures of technological change to explain nonlinearity in estimated returns may be increased by allowing more variation in these variables, e.g., across industries or regions.

Table 3.5: Schedule of the Marginal Rate of Return by Education Level

Previous Education Level <i>Education_t</i>	Full sample			Effects of the Ashenfelters dip	
				$\ln \frac{W_{i,t+s}}{W_{it}}$	$\ln \frac{W_{i,t+s}}{W_{i,t-1}}$
≤ 11	0.0349 (0.0390)	0.0203 (0.0395)	0.0222 (0.0397)	0.0008 (0.0916)	-0.0762 (0.0909)
12	0.0576* (0.0342)	0.0675** (0.0345)	0.0656* (0.0349)	0.0447 (0.0567)	0.0533 (0.0563)
13	0.0768* (0.0453)	0.0792* (0.0452)	0.0806* (0.0461)	0.1455** (0.0705)	0.0843 (0.0700)
14	0.1544*** (0.0384)	0.1390*** (0.0390)	0.1240*** (0.0398)	0.1944*** (0.0648)	0.1331** (0.0623)
15	0.2583*** (0.0505)	0.2136*** (0.0546)	0.2053*** (0.0557)	0.1969** (0.0872)	0.1724** (0.0865)
16	0.0943** (0.0471)	0.0949** (0.0471)	0.0854* (0.0477)	0.1159* (0.0720)	0.1301* (0.0712)
≥ 17	0.1314 (0.0932)	0.1215 (0.0931)	0.1515* (0.0945)	0.1734 (0.1190)	0.1559 (0.1181)
<i>Sheepskin Effect</i>	X	O	O	O	O
<i>Year Dummies</i>	X	X	O	O	O
<i>N</i>	885	885	885	422	422
<i>R²</i>	0.0667	0.0782	0.0963	0.0792	0.0748

Both genders are included in the sample. The dependent variable is change in logarithm of the real hourly rate of pay between the last survey week point before education change and the first survey week point after. Seven dummy variables are created for the former education level (≤ 11 , 12, 13, 14, 15, 16, ≥ 17), interacted with years of education reinvestment, and are included in the wage growth equation along with other control variables: an intercept term, (time distance between the last survey week year (t) before returning to school and the first survey week year ($t+s$) after reemployment), $2 \times Age_t \times S + S^2$, tenure at t , change in the union status between t and $t+s$, and inverse Mills ratio. Numbers in parentheses stand for estimated standard errors. *, **, and *** = significant at the 10%, 5%, and 1% level, respectively.

Table 3.6: Technological Change and Change in the Return to Education

<i>Variables</i>	<i>TFP</i>	<i>R&D RATIO</i>	<i>SCIENTISTS RATIO</i>
<i>Education Level</i>	0.0328** (0.0129)	0.0333*** (0.0129)	0.0357*** (0.0129)
<i>Education Level</i> × <i>ΔTechnology</i>	0.1122 (0.1519)	0.0035 (0.0063)	-0.2991 (0.7513)
<i>ΔEducation</i> (3.7)	0.0729*** (0.0281)	0.0732*** (0.0281)	0.0745*** (0.0280)
<i>N</i>	885	885	885
<i>R</i> ²	0.0831	0.0828	0.0827

Both genders are included in the sample. The dependent variable is change in logarithm of the real hourly rate of pay between the last survey week point before education change and the first survey week point after. $\Delta Technology$ represents a measure of technological change observed for the same period of individual investment. Consequently, these measures vary across individuals depending on starting or ending time points of education investment. The coefficient of the education level represents change in the return to education that is not related with technological change, and the coefficient of the interaction term stands for change in the return to education that is related with concurrent technological change. Each equation also includes an intercept term, S (time distance between the last survey week year (t) before returning to school and the first survey week year ($t+s$) after reemployment), $2 \times Age_t \times S \times S^2$, $Tenure_t$, $\Delta Union$, IMR , a dummy variable for diploma years, and a set of year dummies. Numbers in parentheses stand for estimated standard errors. *, **, and *** = significant at the 10%, 5%, and 1% level, respectively.

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Appendix A

Explaining the Recent Decline of Married Women's Labor Supply: A Cohort Approach

A.1 Changes in the U.S. Tax Structure

The U.S. income tax structure underwent dramatic changes during the 1980s following two monumental legislations, the Economic Recovery Tax Act of 1981 (ERTA81, called Reagan Tax Cut) and the Tax Reform Act of 1986 (TRA86, also called Reagan Tax Cut), which were followed by several additional reforms in 1990, 1993, 1997, 2001, and 2003. The tax reforms in the 1980s substantially lowered marginal statutory tax rates and reduced the number of tax brackets. The latter four reforms are relatively minor changes compared to the ones in the 1980s.

The ERT81 reduced the marginal income tax rate by an average of 23 percent within each tax bracket. In particular, the top bracket rate was reduced from 70 to 50 percent. The most influential tax reform, the TRA86, which went into effect in 1986, broadened the tax base and reduced the number of tax brackets dramatically. Along with the reduction in the number of tax brackets, tax rates were reduced to as low as 38.5 percent at the top bracket. The ETRA86 was also well known for an increase in the capital income tax as

high as 24 percent in the average effective capital tax rate.¹ The Omnibus Budget Reconciliation Act of 1993 increased the number of brackets from three to five, and increased marginal tax rates. The tax rates with 3 brackets ranging from 15 to 31 percent increased to rates with 5 brackets ranging from 15 to 39.6 percent. The Taxpayer Relief Act of 1997 made additional changes to the tax code providing a modest tax cut. The centerpiece of the 1997 Act was a significant new tax benefit to certain families with children through the Per Child Tax credit, which provided a new trend in federal tax policy. Low-income families paid a ‘negative’ income tax, or received a credit in excess of their pre-credit tax liability. Even though this policy change did not directly change the amount of or the number of brackets of the marginal income tax, it affected total amount of tax liabilities for families with children. The Economic Growth and Tax Relief Reconciliation Act of 2001 (called Bush Tax Cut) maintained the number of brackets. But the rate deductions were to be phased in over many years, and the top tax rate would fall from 39.6 percent to 33 percent. It also lowered the amount of tax liabilities from dividends and capital gains. The 2001 tax cut included the expansion of the Per Child Tax Credit from \$500 to \$1,000 per child and increased the Dependent Child Tax Credit. The Jobs and Growth Tax Relief Reconciliation Act of 2003 (also called Bush Tax Cut) continued the Bush Tax Cut of 2001. It continued to accelerate child tax credit and rate reductions which include taxes on capital gains and dividends.

¹ Bosworth and Burtless (1992, p.4-7) provide a detailed description of the ERTA81 and TRA86.

A.2 Population Share of Prime Age (25-59) Married Women by Various Economic/Demographic Groups

Table A.1: Share of Prime Age (25-29) Married Women by Various Groups

	Year						
	1980	1985	1990	1995	2000	2005	2010
<i>A. Education</i>							
High school or less	68.5	62.9	57.8	46.6	43.2	39.2	35.6
Some college or more	31.5	37.1	42.2	53.4	56.8	60.8	64.4
<i>B. Presence of children</i>							
With no children	37.6	40.6	41.6	42.0	43.5	44.3	45.4
With children	62.4	59.4	58.4	58.0	56.5	55.7	54.6
<i>C. Types of marriage</i> ^a							
Wife(<i>H</i>), Husband(<i>H</i>)	50.8	46.3	42.3	31.1	29.1	26.3	24.0
Wife(<i>H</i>), Husband(<i>C</i>)	18.3	17.1	15.6	15.7	14.2	12.8	11.6
Wife(<i>C</i>), Husband(<i>H</i>)	13.9	14.5	12.2	16.1	15.2	16.5	17.5
Wife(<i>C</i>), Husband(<i>C</i>)	17.1	22.2	30.0	37.2	41.5	44.3	46.9
<i>D. Age</i>							
25-29	17.4	17.3	15.4	12.5	11.0	10.6	10.3
30-34	17.7	18.3	18.8	17.3	14.6	13.9	13.1
35-39	15.3	17.0	17.7	18.0	17.4	15.2	14.5
40-44	12.9	13.9	15.4	16.9	17.7	17.0	15.3
45-49	12.3	11.4	12.6	14.8	15.7	16.4	16.5
50-54	12.5	10.9	10.7	11.5	13.2	14.6	16.0
55-59	11.9	11.2	9.4	9.1	10.3	12.5	14.3

Source: The author's calculation using the March Current Population Survey micro data, 1980-2010.

^a *H* and *C* represent 'High school or less' and 'Some college or more', respectively.

A.3 Numerical Method

The household problem is solved numerically by backward recursion from the terminal stage of the life-cycle. I simulate the life-cycle choice of 5,000 individual households and generate streams of permanent shocks to the couple's wages based on the process in Equation (2.11). I solve the value function and optimal policy rule (with a standard approach)

by approximating the solution on a grid given the model parameter values. The parameter values are chosen in the following way. Let $\mathbf{Z} = \{n_{(25-34)}, n_{(35-44)}, n_{(45-49)}, n_y, k, s_{nm}, s_{om}, a_{fb}, n_{ft}, s_{wc}\}$ be a set of moments. $n_{(25-34)}$ represents per capita employment between ages of 25 to 34, $n_{(35-44)}$ the one between ages of 35 and 44, and $n_{(45-49)}$ the one between ages of 45 and 49. n_y is per capita employment of women with children between ages of 0 and 4. k represents the number of children that the wife has until 39. s_{nm} is the share of nonmothers, s_{om} the share of old mothers, and a_{fb} the average age at first childbirth. n_{ft} is per capita full-time employment for ages of 25 to 49 and s_{wc} is the share of wife's wages to child care costs. I solve the following problem to determine 9 parameters $\{\gamma, \lambda, \theta, \phi, g^y, g^m, g^o, \delta, \eta\}$.

$$\min \|\mathbf{Z}^m, \mathbf{Z}^d\|$$

such that

$$\begin{aligned} & \min (n_{(25-34)}^m - n_{(25-34)}^a)^2 + \min (n_{(35-44)}^m - n_{(35-44)}^a)^2 + \min (n_y^m - n_y^a)^2 + \min (k^m - k^a)^2 \\ & + \min (s_{nm}^m - s_{nm}^a)^2 + \min (s_{om}^m - s_{om}^a)^2 + \min (n_{ft}^m - n_{ft}^a)^2 + \min (s_{wc}^m - s_{wc}^a)^2 < \epsilon \end{aligned}$$

where the superscript m represents 'model-generated' and d stands for 'data'. The problem is solved by a multi-dimensional grid search. The grid is defined by multiple dimensions depending on the parameters calibrated. Each dimension has a range of values. Each range is divided into a set of equal-value intervals. The multi-dimensional grid has a centroid which locates the optimum point. The search involves multiple passes. In each pass, I update the least values of the set of parameters and the least value of the function if the value of the function at the node is smaller than the one in the previous node. This method localizes a node with the least function value in each pass. The node producing the least value of the function in each pass becomes the new centroid and builds a smaller grid around it. Successive passes end up shrinking the multi-dimensional grid around the optimum. I iterate the procedure and find the parameter values that minimize the distance between \mathbf{Z}^m and \mathbf{Z}^d .

Finally, I pin down the parameter values and resolve the household problem.

A.4 Estimation Results of Wife's Wage Equation

Table A.2: Estimation Results of Wife's Wage Equation

	1950s	1960s	1970s
β_0	0.9044 (0.0090)	0.8901 (0.0127)	0.8811 (0.0099)
β_1	0.0488 (0.0007)	0.0602 (0.0010)	0.0656 (0.0008)
β_2	-0.00093 (0.00003)	-0.00134 (0.00005)	-0.00155 (0.00004)
β_3	0.0280 (0.0012)	0.0294 (0.0018)	0.0335 (0.0016)
β_4	-0.00209 (0.0001)	-0.00360 (0.00018)	-0.00361 (0.00017)
β_5	-0.0511 (0.0009)	-0.0775 (0.0017)	-0.0772 (0.0015)
β_6	0.00138 (0.00006)	0.00276 (0.00015)	0.0023 (0.00014)
β_7	-0.0057 (0.0010)	0.0041 (0.0016)	0.0134 (0.0014)
β_8	-0.00006 (0.00006)	-0.00083 (0.00011)	-0.00094 (0.00010)
β_9	0.0068 (0.0016)	0.0071 (0.0028)	-0.0116 (0.0024)
β_{10}	0.00146 (0.00013)	0.00259 (0.00026)	0.00307 (0.00023)
β_{11}	-0.0348 (0.0012)	-0.0577 (0.0024)	-0.0556 (0.0022)
β_{12}	0.00092 (0.00008)	0.00203 (0.00021)	0.00280 (0.00020)
β_{13}	-0.0218 (0.0010)	-0.0288 (0.0019)	-0.0332 (0.0016)
ρ	0.8501 (0.0032)	0.8576 (0.0045)	0.8189 (0.0047)
N of obs	7,571	4,507	6,286

Source: The author's estimation using the PSID.
 Estimated standard errors are in parentheses.

Appendix B

Returning to School for Higher Returns

B.1 Discussion of Exclusion Restrictions of Instrumental Variables

In an effort to deal with endogeneity of schooling that arises from unobserved ability and measurement errors, researchers have often used instrumental variables that affect schooling but not earnings conditional on schooling. Examples include school reforms and institutional source of variation of schooling (e.g., minimum school leaving age, tuition costs or geographic proximity of schools), family background (e.g., parents education attainment, number of siblings, birth order), smoking habits, and the use of sample of twins.¹

Recently, Brunello (2002) presents another candidate, individuals attitudes toward risk. Brunello sets up a simple static model, where individual risk aversion affects schooling because it affects the marginal utility of income (and consumption), but does not affect the marginal returns to schooling. He also tests empirically if risk attitude affects the log earnings of individuals with the same education attainment by influencing their occupational choice. Using various definitions of job/occupation, he finds that conditional on schooling and other characteristics, individuals risk attitudes do not affect their occupational choice.

¹ See Card (1999) for a detailed review of these instruments, and Fersterer and Winter-Ebmer (2003) for a review of articles and new evidence that use smoking habits as instruments for education attainment.

Our choice of individuals' risk attitude as an exclusion restriction is primarily motivated by Brunello. Following Brunello, we examine if, conditional on schooling and other characteristics, risk aversion affects individuals' occupation choice. Unlike Brunello, however, in the current study, educational choice depends on individuals' risk attitudes at the time of the choice, not on current risk aversion. As the current study focuses on wage changes generated by education reinvestment, we naturally investigate if, with years of education reinvestment and other characteristics controlled for, individuals' risk attitudes at the time of investment decision make changes to their current occupational choice. However, as noted by Bound et al. (2001) and many other researchers, survey reports of occupations of respondents are subject to great measurement error. In particular, the occurrence of changes in occupation is exaggerated when estimates of such changes are obtained by comparing the reports of the occupations obtained at two points in time. To reduce that type of measurement errors, we adopt five broader occupation categories than those at the 1 digit level.² Then, using our full sample of 885 differenced observations, we run a probit regression of a dummy for occupation change (equals one for changers) against our risk variable along with all the regressors used in our most expanded specification. The p -value of the estimated coefficient of the risk variable is 0.704. We also test if an individual's occupation choice after education reinvestment (at time $t + s$) is affected by their risk attitudes at the time of decision making (t). For that purpose, we run a multinomial logit model of the five occupation dummies against the risk variable along with other control variables. A χ^2 -test cannot reject the null hypothesis of zero coefficients on the risk variable in all four categories at any significance level (p -value=0.369).

We also test directly if individuals' attitudes toward risk at time t are correlated with their wage growth between t and $(t + s)$, conditional on years of reinvestment and other characteristics (so the error term in equation (3.3)). To conduct the Sargan test of over-identifying restrictions, at least two instrumental variables are needed in our case. We follow Evans and Montgomery (1994) and Fersterer and Winter-Ebmer (2003) to use individuals' smoking habits as an additional instrument for education attainment. The idea is that individuals' smoking habits are a good predictor of discount rates, which are not correlated with their (conditional) earnings. Unlike existing studies, however, we consider

² These are (1) professional and managers, (2) sales and clerical, (3) craftsmen, foremen, and operatives, (4) laborers, and (5) service and private household.

individuals' smoking status at the time of decision making, not at an early stage, say age 16. To put it in another way, we consider time-varying as well as time-invariant components of individuals' smoking habits and risk attitudes when using these variables as instruments for education. On the contrary, as existing studies measure individuals' smoking habits or risk attitudes at a point in time, effectiveness of these variables as instruments for education hinges on dominance of the time-invariant component of these variables. On the basis of a reduced sample of 773 observations (due to missing values of respondents smoking status), the Sargan test cannot reject the null hypothesis that both instruments are uncorrelated with the error term (p -value for $\chi^2(1)=0.219$).

Finally, using both instruments, we reproduce Table 3 through 6 and obtain virtually identical results.³

³ These tables, along with a more complete set of test results of the relevance and validity of these instruments, are electronically available upon request.