Parental Choices and the Labor Market Outcome of Children

by

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Abstract

This thesis investigates the dynamics of the effect of parental behavior on the labor market outcome of children and provides a framework for evaluating several policies in an intergenerational context. I focus on the ultimate effect of parental behavior on how children perform once they enter the labor market rather than on the more widely studied effect on children's cognitive achievement. Using the Panel Study of Income Dynamics, I first study the effect of family dissolution during childhood on wages of the second generation using a simple wage regression. The results imply that the event and the timing of family dissolution have significant effects on the wage of next generation. Motivated by these results, a dynamic structural model of the relation between parental choices and labor market outcome of children is studied. I find that not only family disruption but also parents' labor market supply and child bearing decisions play significant roles in determining the future wage of children. Based on this finding, I analyze the choices of parents in which forward looking agents make decisions about labor supply, fertility and family disruption. Parents adjust their behavior taking into consideration not only their own preferences but also the effect these decisions have on the labor market outcome of their children. The recovered preferences are used to conduct policy experiments that evaluate the effects of a baby bonus, a marriage bonus and a parental training program. The results imply that the marriage bonus and the parental training program are effective policies to enhance both the quantity and quality of the next generation while a cash grant for child birth is less effective. I also conduct the experiment that examines an intergenerational changes in wages. The results show that the experiment alters the behavior of parents. When the experiment is understood as a deficit financing, then it implies that the benefits of the policies can be potentially undone by such a financing.

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Contents

List of Tables

List of Figures

Chapter 1

Introduction

The structure of the family and the labor market in the developed world has changed dramatically in the modern era. Women have entered the labor force at unprecedented levels, the frequency of divorce has skyrocketed, and fertility has declined markedly. For example, in the U.S. almost 60% of females are in the labor force compare to one third in 1950, the U.S. divorce rate more than doubled from 1960 to 1980 before a more recent reversal and many developed countries have a fertility rate that is below replacement. While the expanded opportunities for women to work outside the home is almost universally considered a positive development, the high level of divorce and the drop in fertility have raised serious concerns. Children may suffer from family disruption and be affected by change in female labor supply,[1] while the institutional and social infrastructure of the developed world seems heavily dependent on population growth: in the absence of a productive young generation, pay-as-you-go old age support programs face insolvency, and the impressive reductions in poverty rates among the elderly may reverse.

While each of these three developments stands as important in its own right, they are best analyzed in a unified framework. Increased labor market participation by women and more frequent divorce bear a close link even though the direction of causation is unclear. Fertility decisions, too, relate to the set of opportunities available to women, both with respect to the labor market and with respect to divorce. Analyzing policy intended to address problems associated with fertility rates and

[1] Ruhm [2004] documents a small negative relationship between maternal employment and the cognitive ability of children, while Amato [2005] reviews evidence that family disruption is associated with lower achievement by children.

family disruption requires understanding potentially unintended consequences along the other dimensions. For example, a policy designed to increase fertility might lead to behavior that decreases the productivity of the next generation by distorting incentives to invest in parenting, thus partially or fully offsetting any benefits of increased fertility.

Before proceeding to analyze the full dynamic structural model, I first attempt to investigate if family disruption itself has any correlation with future wages of children. This is done by estimating the wage regression of children generation using data from the Panel Study of Income Dynamics (PSID). In this regression, parental divorce is interacted with the independent variables. This simple study reveals that family disruption and when the family disruption event occurs have significant effects on the wage of children, showing the importance of developing a dynamic model to analyze this effect.

In the full dynamic structural model, since I take into account that parents care about the labor market outcome of their children, I first estimate a wage equation which provides an individual fixed effect for each member of the sample. This wage equation provides inputs into the optimization problem of parents (and potential parents) via a parametric "production function" for the individual specific productivity measured by an individual fixed effect and educational achievement of children. I then nonparametrically estimate time investment in children and years children are exposed to family disruption, along with the conditional choice probabilities for labor market participation, divorce, and childbearing. Next, exploiting the methodology developed in Hotz and Miller [1993] and Altug and Miller [1998], I estimate parameters of the utility function of adults. This estimation technique exploits the characteristic of finite state dependence; differences in choices made in a given period can be effectively undone along some path of actions available to agents in the model. Finite state dependence permits consistent estimation of the parameters of the model without the extreme computational burden of repeatedly calculating the value function for each possible set of parameter values. However, one of the crucial decisions that parents make is whether and for how long to expose their children to family disruption in the form of divorce. The decision to divorce or not divorce when a child is at a certain age has a potentially irreversible effect on that child, which renders finite state dependence inapplicable for the divorce decision. By modeling divorce as occurring when the weighted sum of the expected utility of each party is higher as singles than within the marriage, I am able to exploit the presence of divorcees in the panel to identify the model while exploiting the benefits of finite state dependence exhibited by the other discrete choices available. The final estimation step applies a minimum distance estimator to recover the structural parameters.

Having estimated the model, I proceed to describe several policy experiments. Since I model the link between fertility, labor, family disruption and the eventual labor market outcome of children, I am able to include policies that are likely to have important intergenerational effects and are thus difficult to evaluate in a more static framework. Specifically, I consider a baby bonus policy, where the government pays for the birth of new child, that has been implemented several countries experiencing low fertility rates. I investigate another type of cash grant policy, namely a marriage bonus, which is intended to give a couple incentives to get married or remained married. I also consider a government policy of parental training, where the government attempts to increase the productivity of parental time investment in children. Such a policy has the potential to improve labor market outcomes of children and also to stimulate fertility by making the production of "quality" children, who may provide more utility to parents, less expensive. Finally, I examine an intergenerational substitution effect by altering the wage of each generation. One example of such intervention could be a deficit financing of government spending. That is, I posit an income tax reduction for the parent's generation, paid back through an increase in the tax rate on their children. In this context, this intergenerational substitution experiment can serve two purposes. First, it provides some guidance as to how fertility polices and policies designed to improve the prospects of children should be funded. Even an otherwise effective policy could prove counterproductive if the method of funding mostly offsets the salutary effects. Furthermore, the unprecedented levels of deficits in the U.S. make a careful understanding of the dynamics of deficit financing crucial. Given that the U.S., almost uniquely in the developed world, has avoided major drops in fertility, learning whether these financial developments are likely to move the U.S. closer to such an event is important in its own right.

My simulation results show that the most effective way to achieve productive population growth is through the marriage bonus policy. It raises the total fertility rate appreciably while decreasing family disruption, yielding a more productive future generation. Another effective policy is parental training. The effect of a cash grant for child birth turns out to be negligible even at the high end of payments that are currently applied in some countries. According to my estimates, the intergenerational substitution experiment, where the parent generation earns higher wages and the children generation earns lower wages than in the absence of the experiment, decreases the fertility rate and enhance the value of divorce. Therefore, a less productive future generation with reduced size is expected. These findings assert that the cash grant for child birth is not a wise choice and is even worse when the policy is implemented through deficit financing. On the other hand, implementing policies that give monetary incentives to stay married or that enhance the productivity of parenting are better ways to generate more productive population growth.

The thesis is structured as follows. The next chapter briefly reviews relevant literature. Chapter 3 reports the study of family dissolution and children's wage using a simple reduced form approach. The full dynamic structural study of parental choices and the labor market outcome of children is presented in Chapter 4. The following chapter explores the consequences of several policies and an intergenerational substitution experiment using the estimated structural model. Chapter 6 concludes.

Chapter 2

Literature Review

The estimation and policy experiments carried out in this paper draw motivation from evidence relating the outcome of children to the choices and characteristics of parents. The subject of parental influences on children's cognitive achievement has been widely studied; the survey of Haveman and Wolfe [1995] details the literature up to the mid 90s. A recent work by Brown and Flinn [2006] examines how divorce related policies affect the outcome of children by using a model of marital status and investment in children. Another recent work is Tartari [2006], who uses a structural model to disentangle causation and correlation between the observed difference in children's cognitive achievement and the marital status of parents. However, these works neither address the relation between marital status and the ultimate labor market outcome of children nor describe how the attained cognitive outcome would be translated into the labor market outcome which is the main focus of this paper.

There is a significant literature on the relationship between parental labor market decisions and the eventual labor market outcome of children. Much of this research focuses on income mobility; for example, Solon [1992] examines the income mobility between generations in the U.S. and in a separate paper with Chadwick and Solon [2002] the income mobility of daughters is studied. The study of the effect of family disruption on children's later labor market outcome is relatively limited and mostly done in sociology. The findings are not consistent; for example, Krein [1986] finds that the negative effect of a single parent family on earnings of males is through education, Amato and Keith [1991] examine differences in the effect of family disruption by race and sex and find no evidence of a negative effect of family disruption for minority males and Powell and Parcel [1997] assert that the negative effect of family disruption on earnings occurs through education for females but not for males. Fronstin, Greenberg, and Robins [2001] find a slightly negative effect of parental disruption on the employment of males while the effect on females' wage rate is substantial. On the other hand, after controlling various family backgrounds and incorporating the death of parent, Lang and Zagorsky [2000] conclude that there is no significant effect of being raised in a single-parent family on the earnings of children. More recently, Gruber [2001] examines the consequences of unilateral divorce and finds that children exposed to easier divorce laws have lower income as adults. Since these studies mostly focus on cross sectional data and often ignore the timing of family disruption, I conduct a separate regression study on the effect of family disruption on the wage of children using panel data which considers the timing of family disruption. This can be found in the next chapter. According to the study, the magnitude and direction of the effect are not uniform across race and gender. However, the study shows that family disruption itself and its timing has a significant effect on children's future wage. This further motivates constructing and estimating a dynamic model of family disruption and the labor market outcome of children.

I develop a dynamic structural model of labor force participation, fertility, and divorce. The dynamics of female labor supply and fertility have been widely studied. For example, while Heckman and MaCurdy [1980] studies female labor supply in a life cycle model, Wolpin [1984] and Hotz and Miller [1993] investigate the dynamic structural model of fertility in the context of either mortality or contraception. Rosenzweig and Wolpin [1980] and Heckman and Walker [1990] relate fertility and female labor in a life-cycle model, and structural models of this are studied in Hotz and Miller [1988], Eckstein and Wolpin [1989] and more recently Gayle and Miller [2006]. However, most of the models adopted in these studies treat the husband's choice exogenous, focusing on female's behavior. This feature restricts the possibility of exploring the marital dissolution which I address as one of main choices. Also, the models do not study the benefits children can bring into parents in detail.[1] A recent paper by Tartari [2006] does consider these two factors, namely the divorce choice and children's outcomes, using a dynamic model of the household. However, the focus of her study is on the cognitive ability of children, as measured by the score on standardized test. In my model, parents care about the labor market outcome of their children

[1] For example, Eckstein and Wolpin [1989] leave the utility component from children unspecified and use non-fertile periods only to estimate the model.

and take this into account when making decisions about further childbearing, labor market participation, and family disruption. In contrast to much of the literature on family disruption, including Tartari [2006], I focus on evaluating the long-term effects on children once they enter the labor market rather than on potentially transitory effects on school performance, psychological well-being, or standardized testing. This both provides a more natural model of parental concern for children and permits evaluation of policies with important intertemporal implications.

Chapter 3

Family Dissolution and Children's Wages

This section discusses the relation between family disruption and labor market outcome of children using reduced form analysis with (1) panel data to control for individual heterogeneity and aggregate shocks and (2) new indicators controlling for the timing of the family disruption event.

3.1 Data

Two sets of data are used in this study; Data Set I and Data Set II both of which come from PSID data between 1968 and 2000.[1] The first data set contains more observations because it makes use of responses to the questionnaire of "Were you living with both your natural parents most of the time until you were age 16?" to determine if an individual is from a disrupted family.[2] Data Set II is also based on PSID data but the indicator variable for coming from broken family is constructed by comparing parents' ID and their living arrangement. This requires a perfect history of living arrangements of parents at least since the child was born. In other words, the parents and the child should be in the PSID sample and the child should participate in the workforce at some point during the study period. This reduces the sample

[1]Note that PSID changes the data collecting scheme from annual to biannual since 1999. Fortunately the labor data between years of 1998 and 2000 are provided by 'T-2 Individual Income Files: 1999 and 2001' although its level of confidence is lower than usual waves since it asks respondents about the labor market activities two years ago.

[2]This variable is also used in the analysis of Powell and Parcel [1997].

size quite a lot. The sample size used in the estimation is 2074 for males and 2224 for females while the relevant sizes of Data Set I are 6482 for males and 5844 for females. In spite of this reduced sample size, Data Set II has one major advantage. By tracing how parents behave in terms of family structure, it is possible to construct the indicator of being from a broken family by the age range of children. That is, other than the indicator of "living with birth parents up to 18 years" which is labeled as 'Broken' I construct three additional indicators of "experiencing family disruption between the birth and age 5," "experiencing family disruption between age 6 and age 10," and "experiencing family disruption between age 11 and age 18." I designate the first one to be 'BrokenY,' the second one 'BrokenM' and the third one 'BrokenO.' In this way, I can study the importance of the timing of family disruption in the childhood. The need to consider this issue has been stressed in the literature.[3]

The general description of Data Set I for selective years is provided in Table 3.1. Non-black males from a disrupted family are on average less educated, less likely to get married, less likely to participate the labor market, and work less. The real wage is less for those people except in the 1970s which can be attributed to the changing reasons for family disruption. That is, the cause of separation of parents is less likely to be linked to conflicts than to a deceased partner in those period. However, as time passes the discrepancy of wages in favor of males from an intact family becomes apparent. Non-black females from a broken family exhibit a similar pattern to non-black males except that they are more likely to participate the labor market in 1990s and they work more than those from an intact family in the 1970s. Also there is an apparent time trend in the wage difference, as in the case of non-black males. For black males, the pattern is not as consistent as non-black males. Although the marriage rate and hours worked for males from an intact family are always higher than those from a broken family, the education level and labor market participation rate do not show a consistent relationship between the two groups. A similar observation applies for black females. Table 3.2 shows the statistics of Data Set II. Because of the need to get an indicator of family disruption by age range of children the sample is on average younger and the dispersion of age is much smaller than in Data Set I. For non-black males from an intact family, the pattern of higher education attainment, higher participation rate and higher wage is the same as in Data Set I. Non-black females do not show consistent differences between broken and

[3] See, for example, Biblarz and Raftery [1993].

intact families in participation rates over time. Those who do participate work more and earn more when from an intact family. One interesting observation is that black males from a broken family attain a higher education level, while the case is opposite for black females. But the sample size for these observations is small. Black people from broken families work less but the wage rate is not always lower than those from intact families.

3.2 Estimation

A simple reduced form wage equation is estimated. The dependent variable is log wage and the independent variables are age squared, age multiplied by the level of completed education, lagged participation indicators up to three years ago and lagged work experiences up to three years ago. For each year the wage above the top 1% and below bottom 1% are trimmed.[4] These independent variables are also interacted with an indicator of being from disrupted family so that the effect of broken family can be examined. For Data Set I, only one indicator of being from a broken family can be used. For Data Set II, four kinds of indicators are examined as described in the earlier section. The estimation is done using the first differencing method with panel data.

For each gender/race combination, the estimation results of Data Set I are provided in Table 3.3. The top panel is the estimated coefficients of the independent variables without interacting with the broken family indicator. Overall there are positive returns from previous work experiences and negative coefficients from past participation. The age effect is confirmed to be concave and education plays a role in determining the wage. These results are in line with previous literature. When the effects are examined by interacting with the 'Broken' indicator (shown in the lower panel of the table) the results vary by gender and by race. First, family disruption decreases the returns from previous work experience for non-black people. However, the case is reversed for black people. In general, family disruption increases the threshold that needs to be overcome to participate the labor market. Finally, the effect of education is influenced by family disruption for non-black people, and the direction is different by gender.

Table 3.4 presents the estimation results using male data from Data Set II . Re-

[4] It seems that the results are a bit sensitive to how much and how to trim the outliers.

gardless of race and without interacting with any indicators of family disruption, the estimated coefficients are consistent with general expectations in terms of past work experiences, participation decisions, age and education, although the magnitudes differ by race. The first column of non-black males shows the negative effects of coming from a disrupted family on some of work experiences and participation decisions. However, the coefficients of age squared or education are not affected by family disruption. Note that the results are different from the first column of Table 3.3 due to the fact that this results come from a younger and smaller sample. The returns from previous experience are reduced if one has an event of family disruption between birth and the age of five (the second column). The effect is very strong. For example, the experience two years ago plays very little role once family disruption is interacted. However if family disruption occurs between the age of six and ten (the third column), then the effect is reversed and this reversed effect is fairly large. In fact, the returns from previous experience a year ago is the largest for this group of people. Even though it increases the threshold for participating in workforce, the results are still surprising. When family disruption happens while the child is between age 10 and 18 (the fourth column), the effect of family disruption is similar to the overall effect, shown in the first column. For black males, family disruption negatively affects the return of work experience two years ago but decreases the size of the threshold to enter labor market. These directions are opposite to the results of the second column of Table 3.3 in which Data Set I is used. One possible reason is the difference between sample sizes. For this group of people, Data Set I provides 1825 individual while Data Set II has only 554 observations. When 'BrokenY' is used, the effect of family disruption is confounding. It decreases the return two years ago by quite a big magnitude while it enhances the effect of experience a year ago and three years ago. Experiencing family disruption in the middle or later part of childhood negatively affects the return of work experience. For example, the effect of experience three years ago even becomes negative when interacted with 'BrokenO.' Also it negatively affects how education alters productivity. A general observation is that the effect of experiencing family disruption during any period of childhood affects black males by a larger magnitude than non-black males, at least for the case of work experience. This holds for effects in either direction.

Table 3.5 shows the results for females. Again the coefficients in the upper panels confirm the standard results. For non-black females, coming from a disrupted family in any time of her childhood decreases the effect of work experience while it increases the threshold to participate (the first column). When one experiences disruption early in childhood, it greatly reduces the returns of past work experience and even makes the return from experience three years ago negative (the second column). However it increases the effect of education by a lot. On the contrary, experiencing family disruption in the later part of childhood increases the return of work experience and makes people much more likely to participate in the labor market. However, the effect of education becomes almost nil. For black females, the effect of family disruption from early childhood decreases the effects of work experience a lot, even making the returns from two and three years ago negative. The experience of disruption during the middle or later childhood does not seem to matter for this group of people. However, again note that the direction is reversed when compared with the results using Data Set I in which black females show positive effect of family disruption on work experience. In summary, these results confirms the importance of the timing of experiencing the event of family disruption. Different timing yields different directions of the effect of family disruption. The magnitude of the various effects also differs by a lot. It is surprising that experiencing family disruption between age 6 and 10 for non-black males and experiencing disruption later in childhood for non-black females increases the returns of past work experience. The effect of education is more relevant for females than males as the previous study of Powell and Parcel [1997] has asserted. However the direction is again confounded by the timing of the occurrence of the event.

It should be noted that there are other factors through which parents can influence children. For example, parents' labor supply decisions and having more siblings in a family along with family disruption can make a child's future wage better or worse off. Even though the estimation presented in this section only shows the importance of family disruption, the structural model in the next chapter introduces the parents' decision over divorce (family disruption), labor supply and child bearing to disentangle the relation between parents' actions and the labor market outcome of children.

Table 3.1: Summary Statistics of Data Set I

	Non-black Males						Black Males					
	Non-broken			Broken			Non-broken			Broken		
Variables	1977	1987	1997	1977	1987	1997	1977	1987	1997	1977	1987	1997
Num. observations	1902	2642	2463	392	512	520	533	808	478	282	510	338
Age	38.86	41.84	44.80	39.32	42.89	43.20	37.78	39.88	44.49	36.44	37.45	41.82
	(14.50)	(14.94)	(14.68)	(14.18)	(15.42)	(15.28)	(13.94)	(14.01)	(13.74)	(13.95)	(13.33)	(12.46)
Education	13.11	13.34	13.42	12.62	12.84	13.03	10.95	11.74	12.37	11.21	11.96	12.34
	(2.703)	(2.473)	(2.658)	(3.036)	(2.828)	(2.553)	(3.242)	(2.781)	(2.532)	(3.071)	(2.673)	(2.238)
Married	0.854	0.818	0.781	0.832	0.807	0.714	0.737	0.668	0.659	0.667	0.598	0.589
	(0.353)	(0.386)	(0.414)	(0.375)	(0.395)	(0.453)	(0.441)	(0.471)	(0.475)	(0.472)	(0.491)	(0.493)
Num. young child	0.162	0.120	0.101	0.089	0.111	0.137	0.190	0.145	0.092	0.174	0.159	0.101
	(0.387)	(0.342)	(0.316)	(0.286)	(0.327)	(0.365)	(0.429)	(0.386)	(0.297)	(0.415)	(0.402)	(0.320)
Whether work	0.927	0.869	0.804	0.903	0.828	0.796	0.895	0.809	0.713	0.908	0.835	0.710
	(0.260)	(0.338)	(0.397)	(0.296)	(0.378)	(0.403)	(0.307)	(0.393)	(0.453)	(0.290)	(0.371)	(0.454)
Hours worked	2179	2194	2238	2171	2174	2140	2013	2037	2125	1933	1980	2015
	(714.6)	(694.2)	(615.8)	(701.6)	(697.0)	(647.8)	(683.5)	(712.4)	(594.0)	(674.0)	(708.3)	(698.1)
Wage (real)	19.71	19.35	20.46	19.90	18.38	17.96	14.52	13.92	15.26	14.65	13.50	15.00
	(9.870)	(10.71)	(12.88)	(10.68)	(10.84)	(12.14)	(7.210)	(8.228)	(8.515)	(7.808)	(8.333)	(8.281)
	Non-black Females						Black Females					
	Non-broken			Broken			Non-broken			Broken		
Variables	1977	1987	1997	1977	1987	1997	1977	1987	1997	1977	1987	1997
Num. observations	2151	2787	1976	532	674	534	786	1087	645	542	770	563
Age	40.14	43.56	48.92	39.42	42.25	44.10	38.66	41.33	44.45	37.77	39.71	41.17
	(15.98)	(16.57)	(15.88)	(15.11)	(16.33)	(17.18)	(14.13)	(15.06)	(14.54)	(14.06)	(14.86)	(14.43)
Education	12.71	13.03	13.42	12.01	12.43	12.81	11.35	11.87	12.39	11.26	11.92	12.38
	(2.551)	(2.415)	(2.404)	(2.685)	(2.514)	(2.364)	(2.656)	(2.546)	(2.233)	(2.572)	(2.378)	(2.165)
Married	0.769	0.742	0.650	0.714	0.693	0.577	0.566	0.459	0.364	0.515	0.422	0.329
	(0.422)	(0.437)	(0.477)	(0.452)	(0.462)	(0.495)	(0.496)	(0.499)	(0.482)	(0.500)	(0.494)	(0.470)
Num. young child	0.132	0.102	0.047	0.135	0.135	0.112	0.148	0.118	0.071	0.162	0.127	0.103
	(0.348)	(0.314)	(0.218)	(0.364)	(0.395)	(0.345)	(0.383)	(0.365)	(0.264)	(0.389)	(0.353)	(0.332)
Whether work	0.601	0.660	0.620	0.596	0.651	0.631	0.621	0.648	0.589	0.616	0.675	0.615
	(0.490)	(0.474)	(0.486)	(0.491)	(0.477)	(0.483)	(0.486)	(0.478)	(0.492)	(0.487)	(0.469)	(0.487)
Hours worked	1394	1593	1737	1410	1590	1731	1498	1655	1801	1450	1505	1733
	(748.3)	(728.1)	(678.3)	(728.6)	(741.8)	(681.2)	(641.9)	(670.6)	(554.7)	(633.1)	(728.8)	(745.1)
Wage (real)	12.93	13.52	15.72	11.79	12.07	12.70	10.28	10.87	11.93	10.69	10.40	12.18
	(7.687)	(8.477)	(11.09)	(6.681)	(7.551)	(8.305)	(5.646)	(6.940)	(6.761)	(6.031)	(6.275)	(7.663)

Table 3.2: Summary Statistics of Data Set II

	Non-black Males						Black Males					
	Non-broken			Broken			Non-broken			Broken		
Variables	1977	1987	1997	1977	1987	1997	1977	1987	1997	1977	1987	1997
Num. observations	426	832	836	84	199	186	126	285	166	44	150	74
Age	26.09	31.73	37.60	24.67	29.22	33.91	26.44	31.25	38.49	24.73	29.87	36.97
	(4.702)	(6.271)	(8.757)	(4.303)	(5.995)	(8.540)	(5.340)	(6.231)	(6.979)	(2.983)	(4.719)	(7.115)
Education	13.71	13.73	13.89	13.42	13.14	13.31	12.14	12.42	12.64	12.93	12.76	12.82
	(2.210)	(2.118)	(2.118)	(2.381)	(2.155)	(1.964)	(2.123)	(1.940)	(1.792)	(2.005)	(1.805)	(1.919)
Whether work	0.981	0.976	0.943	0.964	0.955	0.936	0.944	0.898	0.861	0.932	0.913	0.730
	(0.136)	(0.153)	(0.233)	(0.187)	(0.208)	(0.246)	(0.230)	(0.303)	(0.347)	(0.255)	(0.282)	(0.447)
Hours worked	2149	2204	2281	2187	2154	2165	1943	2052	2127	1874	2007	2042
	(656.1)	(613.5)	(558.5)	(776.5)	(595.4)	(549.3)	(626.7)	(691.2)	(631.4)	(776.8)	(742.3)	(789.0)
Wage (real)	17.07	17.96	20.61	15.31	16.54	17.44	13.23	12.57	14.91	14.44	12.03	15.23
	(7.125)	(9.349)	(12.84)	(7.132)	(9.414)	(11.47)	(6.188)	(7.443)	(8.324)	(7.114)	(7.684)	(9.932)

	Non-black Females						Black Females					
	Non-broken			Broken			Non-broken			Broken		
Variables	1977	1987	1997	1977	1987	1997	1977	1987	1997	1977	1987	1997
Num. observations	421	819	791	102	267	233	177	431	322	81	227	148
Age	24.87	30.56	36.57	24.36	28.31	33.52	24.87	30.47	36.98	26.04	29.92	36.32
	(4.948)	(6.054)	(8.261)	(5.181)	(6.406)	(8.559)	(4.903)	(6.252)	(7.719)	(6.045)	(6.721)	(7.422)
Education	13.52	13.66	14.04	13.08	13.10	13.52	12.59	12.84	12.99	12.54	12.67	12.74
	(2.188)	(2.097)	(2.087)	(2.128)	(2.080)	(2.083)	(1.763)	(1.791)	(1.961)	(1.943)	(1.729)	(1.626)
Whether work	0.763	0.824	0.810	0.745	0.832	0.837	0.780	0.798	0.736	0.704	0.749	0.689
	(0.426)	(0.381)	(0.392)	(0.438)	(0.375)	(0.370)	(0.416)	(0.402)	(0.442)	(0.460)	(0.435)	(0.464)
Hrs worked	1456	1647	1761	1357	1579	1716	1534	1675	1837	1529	1513	1662
	(697.9)	(730.7)	(717.4)	(691.9)	(700.0)	(675.8)	(635.0)	(686.5)	(633.9)	(584.1)	(695.3)	(684.8)
Wage (real)	12.41	13.40	16.11	10.89	11.61	12.73	10.19	10.78	12.20	11.46	9.740	11.50
	(6.477)	(7.706)	(11.04)	(6.008)	(6.854)	(9.071)	(5.355)	(6.788)	(6.703)	(6.032)	(5.659)	(7.271)

Table 3.3: Wage Equation Estimation using Data Set I

		Males				Females			
		Non-black		Black		Non-black		Black	
Variables		Est.	s.e.	Est.	s.e.	Est.	s.e.	Est.	s.e.
Experience	hrs worked (L1)	0.9303*	0.0181	0.6890*	0.0324	1.2120*	0.0240	1.0767*	0.0374
	hrs worked (L2)	0.5186*	0.0181	0.5058*	0.0333	0.5219*	0.0242	0.5748*	0.0385
	hrs worked (L3)	0.2462*	0.0174	0.3485*	0.0323	0.2693*	0.0238	0.2856*	0.0376
	dwork (L1)	-0.0342*	0.0120	0.0384*	0.0175	-0.0254*	0.0061	-0.0819*	0.0100
	dwork (L2)	-0.0833*	0.0116	-0.0807*	0.0172	-0.0527*	0.0062	-0.0730*	0.0102
	dwork (L3)	0.0154	0.0107	-0.0764*	0.0162	-0.0364*	0.0058	-0.0363*	0.0094
Age squared		-0.0005*	0.0000	-0.0004*	0.0001	-0.0003*	0.0000	-0.0003*	0.0001
Age × edu		0.0011*	0.0002	0.0005	0.0004	0.0004	0.0004	0.0017*	0.0005
×Broken									
Experience	hrs worked (L1)	-0.0249	0.0425	0.1562*	0.0525	-0.1956*	0.0497	0.1800*	0.0560
	hrs worked (L2)	-0.1624*	0.0429	0.1642*	0.0543	0.0477	0.0508	0.0138	0.0579
	hrs worked (L3)	-0.0414	0.0415	-0.0096	0.0522	-0.0670	0.0497	0.0267	0.0566
	dwork (L1)	-0.1310*	0.0306	-0.1743*	0.0279	-0.0883*	0.0133	-0.0347*	0.0147
	dwork (L2)	0.0285	0.0290	-0.0580*	0.0280	-0.0705*	0.0133	-0.0191	0.0149
	dwork (L3)	-0.0689*	0.0259	-0.0426	0.0259	-0.0190	0.0124	0.0147	0.0140
Age squared		0.0001*	0.0001	0.0000	0.0001	-0.0001	0.0001	-0.0000	0.0001
Age × edu		-0.0009*	0.0003	-0.0004	0.0004	0.0010*	0.0004	0.0001	0.0005

The number of individuals: Males/Non-black: 4657, Males/Black: 1825, Females/Non-black: 3727, Females/Black: 2117

* Significant at 5 % level

Table 3.4: Wage Equation Estimation using Data Set II - Males

		Non-black						
	Broken		BrokenY		BrokenM		BrokenO	
Variables	Est.	s.e.	Est.	s.e.	Est.	s.e.	Est.	s.e.
Experience hrs worked (L1)	0.8835*	0.0298	0.8976*	0.0273	0.8760*	0.0281	0.8844*	0.0298
hrs worked (L2)	0.6068*	0.0294	0.5930*	0.0272	0.5771*	0.0277	0.5986*	0.0295
hrs worked (L3)	0.3195*	0.0273	0.3267*	0.0253	0.3213*	0.0258	0.3185*	0.0274
dwork (L1)	0.0059	0.0222	-0.0410*	0.0205	-0.0271	0.0208	-0.0011	0.0220
dwork (L2)	-0.0400*	0.0201	-0.0461*	0.0184	-0.0332	0.0188	-0.0511*	0.0197
dwork (L3)	0.0044	0.0176	-0.0115	0.0164	-0.0099	0.0166	-0.0059	0.0174
Age squared	-0.0010*	0.0001	-0.0010*	0.0001	-0.0010*	0.0001	-0.0010*	0.0001
Age × edu	0.0041*	0.0005	0.0041*	0.0005	0.0042*	0.0005	0.0041*	0.0005
×Broken								
Experience hrs worked (L1)	0.0626	0.0648	-0.3108*	0.1319	0.5868*	0.1222	-0.0128	0.0840
hrs worked (L2)	-0.1334*	0.0658	-0.5309*	0.1297	0.4504*	0.1336	-0.1733*	0.0846
hrs worked (L3)	-0.0144	0.0621	-0.1072	0.1213	0.0636	0.1236	-0.0192	0.0804
dwork (L1)	-0.2717*	0.0502	0.0546	0.1014	-0.2469*	0.1139	-0.3176*	0.0618
dwork (L2)	-0.0407	0.0431	0.0312	0.0774	-0.2463*	0.0906	0.0322	0.0559
dwork (L3)	-0.1776*	0.0364	-0.1270*	0.0644	-0.2874*	0.0707	-0.1110*	0.0484
Age squared	0.0001	0.0002	0.0007	0.0004	0.0003	0.0003	-0.0002	0.0002
Age × edu	-0.0004	0.0008	-0.0032	0.0020	-0.0016	0.0016	0.0010	0.0010

		Black						
	Broken		BrokenY		BrokenM		BrokenO	
Variables	Est.	s.e.	Est.	s.e.	Est.	s.e.	Est.	s.e.
Experience hrs worked (L1)	1.0251*	0.0508	1.0029*	0.0456	1.1059*	0.0461	1.0038*	0.0473
hrs worked (L2)	1.0286*	0.0518	0.9194*	0.0463	1.0068*	0.0465	0.9331*	0.0486
hrs worked (L3)	0.3280*	0.0488	0.3042*	0.0434	0.3267*	0.0429	0.3029*	0.0451
dwork (L1)	-0.0898*	0.0283	-0.0334	0.0268	-0.0085	0.0264	-0.0988*	0.0266
dwork (L2)	-0.1443*	0.0260	-0.1280*	0.0243	-0.1504*	0.0243	-0.1197*	0.0246
dwork (L3)	-0.0941*	0.0241	-0.1160*	0.0219	-0.1285*	0.0215	-0.0895*	0.0225
Age squared	-0.0004*	0.0002	-0.0004*	0.0002	-0.0004*	0.0002	-0.0004*	0.0002
Age × edu	0.0024*	0.0009	0.0011	0.0009	0.0012	0.0009	0.0027*	0.0009
×Broken								
Experience hrs worked (L1)	-0.0113	0.0954	0.5207*	0.1483	-0.4572*	0.1431	-0.2275	0.1496
hrs worked (L2)	-0.6688*	0.0973	-0.4679*	0.1626	-0.7185*	0.1487	-0.6113*	0.1416
hrs worked (L3)	-0.0283	0.0898	0.5709*	0.1461	-0.1526	0.1432	-0.4138*	0.1270
dwork (L1)	0.0329	0.0471	-0.0037	0.0733	-0.2373*	0.0805	0.1288*	0.0629
dwork (L2)	0.0931*	0.0444	0.1425	0.0740	0.0871	0.0753	-0.0419	0.0590
dwork (L3)	0.0699	0.0412	0.0171	0.0623	0.0116	0.0712	0.1547*	0.0568
Age squared	0.0002	0.0003	-0.0007	0.0004	-0.0003	0.0005	0.0012*	0.0005
Age × edu	-0.0009	0.0014	0.0033	0.0020	0.0012	0.0023	-0.0053*	0.0023

- Broken: "living with birth parents up to 18 years," BrokenY: "experiencing family disruption between the birth and age 5," BrokenM: "experiencing family disruption between age 6 and age 10," BrokenO: "experiencing family disruption between age 11 and age 18."
- The number of individuals: Non-black/Broken: 1520, Non-black/BrokenY: 1495, Non-black/BrokenY: 1452, Non-black/BrokenY: 1406, Black/Broken: 554, Black/BrokenY: 520, Black/BrokenM: 505, Black/BrokenO: 491
* Significant at 5% level

Table 3.5: Wage Equation Estimation using Data Set II - Females

	Non-black							
	Broken		BrokenY		BrokenM		BrokenO	
Variables	Est.	s.e.	Est.	s.e.	Est.	s.e.	Est.	s.e.
Experience hrs worked (L1)	1.5670*	0.0369	1.5238*	0.0330	1.5339*	0.0344	1.5064*	0.0360
hrs worked (L2)	0.4333*	0.0379	0.4922*	0.0338	0.5003*	0.0353	0.4399*	0.0370
hrs worked (L3)	0.2333*	0.0361	0.2497*	0.0323	0.2279*	0.0336	0.2455*	0.0353
dwork (L1)	-0.1174*	0.0104	-0.1027*	0.0095	-0.1013*	0.0097	-0.1171*	0.0103
dwork (L2)	-0.0990*	0.0101	-0.1019*	0.0093	-0.1056*	0.0095	-0.1026*	0.0100
dwork (L3)	-0.0594*	0.0094	-0.0714*	0.0086	-0.0670*	0.0088	-0.0636*	0.0093
Age squared	-0.0003*	0.0001	-0.0002	0.0001	-0.0002	0.0001	-0.0003*	0.0001
Age × edu	0.0018*	0.0007	0.0014*	0.0007	0.0016*	0.0007	0.0023*	0.0007
×Broken								
Experience hrs worked (L1)	-0.4124*	0.0732	-0.6939*	0.1491	-0.4818*	0.1123	-0.1163	0.1016
hrs worked (L2)	0.0835	0.0757	-0.2626	0.1637	-0.0558	0.1139	0.3155*	0.1044
hrs worked (L3)	-0.1007	0.0725	-0.3464*	0.1604	0.2113	0.1138	-0.1866	0.0972
dwork (L1)	0.0627*	0.0225	-0.1021*	0.0456	-0.0054	0.0446	0.1164*	0.0290
dwork (L2)	-0.0296	0.0222	0.0239	0.0447	0.0833*	0.0414	-0.0929*	0.0293
dwork (L3)	-0.0121	0.0201	0.0622	0.0430	-0.1063*	0.0372	0.0115	0.0261
Age squared	0.0000	0.0002	-0.0013*	0.0004	0.0003	0.0003	0.0004	0.0003
Age × edu	0.0003	0.0009	0.0076*	0.0019	-0.0004	0.0016	-0.0023*	0.0012

	Black							
	Broken		BrokenY		BrokenM		BrokenO	
Variables	Est.	s.e.	Est.	s.e.	Est.	s.e.	Est.	s.e.
Experience hrs worked (L1)	1.2749*	0.0504	1.2934*	0.0439	1.2290*	0.0455	1.2226*	0.0469
hrs worked (L2)	0.6602*	0.0504	0.6288*	0.0442	0.6464*	0.0457	0.5920*	0.0478
hrs worked (L3)	0.2347*	0.0483	0.1796*	0.0428	0.2005*	0.0438	0.2230*	0.0460
dwork (L1)	-0.0859*	0.0142	-0.0967*	0.0124	-0.0700*	0.0127	-0.0805*	0.0135
dwork (L2)	-0.1081*	0.0136	-0.0955*	0.0117	-0.1059*	0.0121	-0.1240*	0.0131
dwork (L3)	-0.0471*	0.0119	-0.0535*	0.0104	-0.0475*	0.0107	-0.0416*	0.0115
Age squared	-0.0006*	0.0002	-0.0006*	0.0001	-0.0005*	0.0002	-0.0006*	0.0002
Age × edu	0.0028*	0.0010	0.0034*	0.0009	0.0030*	0.0010	0.0025*	0.0010
×Broken								
Experience hrs worked (L1)	-0.2080*	0.0863	-0.4594*	0.1426	-0.0669	0.1221	-0.0849	0.1266
hrs worked (L2)	-0.2781*	0.0886	-0.8384*	0.1500	-0.1933	0.1324	0.0920	0.1248
hrs worked (L3)	-0.2267*	0.0864	-0.4900*	0.1401	-0.1232	0.1351	-0.1158	0.1222
dwork (L1)	0.0178	0.0232	0.0032	0.0370	-0.0188	0.0354	0.0330	0.0322
dwork (L2)	-0.0059	0.0227	0.0040	0.0378	-0.0323	0.0331	0.0144	0.0321
dwork (L3)	-0.0018	0.0205	0.0720*	0.0341	-0.0210	0.0302	-0.0148	0.0294
Age squared	-0.0001	0.0002	0.0009*	0.0004	-0.0004	0.0003	-0.0003	0.0003
Age × edu	0.0008	0.0011	-0.0027	0.0019	0.0023	0.0015	0.0010	0.0016

- Broken: "living with birth parents up to 18 years," BrokenY: "experiencing family disruption between the birth and age 5," BrokenM: "experiencing family disruption between age 6 and age 10," BrokenO: "experiencing family disruption between age 11 and age 18."

- The number of individuals: Non-black/Broken: 1466, Non-black/BrokenY: 1435, Non-black/BrokenY: 1383, Non-black/BrokenY: 1326, Black/Broken: 758, Black/BrokenY: 712, Black/BrokenM: 691, Black/BrokenO: 675

* Significant at 5% level

Chapter 4

Structural Estimation of Parental Choices and the Labor Market Outcome of Children

This chapter explores the dynamics of parental choices and the labor market outcome of children. Motivated by the previous chapter, the following study explicitly incorporates parental choices and the timing of these choices. It extends the scope of parental choices to labor supply, family dissolution and child birth. Parents who recognize the importance of their choices on children's future outcome and behave accordingly, considering both their own utility and the utility they can get from their children.

4.1 Data

The data used in the following structural model is constructed from the Individual File, Family File, Childbirth and Adoption History File, Marriage History File, Parent Identification File and T-2 Individual Income File from PSID. All individuals in the sample are either "Head" or "Wife" of a family at least at some point during the study period from 1968 to 2000. From the Individual File and the Family File, anyone who has missing values on race, age, or education level are identified and excluded.[1] Also

[1]The education data is inconsistent and incomplete. For example some respondents report the education level in a year which is lower than they have reported in previous years. Hence, the maximum of a respondent's reported levels of education is used as the level of education in this

individuals with missing labor market data such as participation, hours worked or wage are dropped from the sample. Due to the change from an annual to a bi-annual survey for the PSID starting in 1999, T-2 Individual Income File is used to construct the labor market data for 1998 and 2000. By using the Marital History File, individuals with uncertain marriage/separtion date(s) are excluded. The number of children and birth decisions are traced from the Childbirth and Adoption History file and Parent Identification File. The sample after these treatments is referred to as the full sample. The annual summary statistics of the main variables are presented in columns called Full in Table 4.3, Table 4.4 and Table 4.5. One noticeable trend is the change in the labor market participation rates. The participation rate of males dropped from 98% to 85% during the study period while that of females has increased from 61% to 73%. Also the hours worked for females has increased by more than 32%. The education level of both genders has increased by on average more than two years during the study period. The data set also reflects the pervasive trend toward having fewer children.

4.1.1 Sample selection

To analyze household behavior within the framework developed in this paper, it is necessary to select subsample from the full sample. Several restrictions on the full sample define the subsample. The restrictions are as follows: 1) An individual has to participate in the labor market at some point during the study period. This is required to recover the individual fixed effects that are used throughout the paper. 2) The subsample is composed of people who are currently married or who are divorced. This means that people who have never married are not in the subsample. Since the remarriage is not modeled in my study, people are excluded from the subsample from the point when they remarry. 3) If an individual is married in a certain year and his or her spouse's information is not complete, he or she is excluded in that year. That is, even though the individual provides all necessary information for the variables relevant to himself or herself, if his or her spouse's variables are missing, the individual cannot be in the subsample. This criterion along with the previous one reduces the size of subsample by a lot but these treatments are necessary. 4) To have a reasonable size of state variables, the maximum number of children is set to

study.

three. 5) If an individual's hourly wage is more than \$1000 or less than \$0.5, or if one works without monetary compensation in a certain year, he or she is excluded from the subsample in that particular year. 6) If the separation is due to the death of a spouse, the individual is not recognized as a divorcee as the action of divorcing is a choice variable in my model.

The descriptive statistics of the subsample for the main variables are presented in Table 4.3, Table 4.4 and Table 4.5 under the column called Sub. Compared to the full sample, the size of subsample is much smaller. This feature is the most apparent for the initial periods. This is partly due to the fact that many females in earlier periods never enter the labor market in the study period. As they do not provide labor market variables necessary for this study, they are not in the sample, nor are their husbands. This also explains why the subsample is younger than the full sample. Older married females are less likely to be involved in the labor market.

Compared to the full sample, the education level for each gender is higher and the education level difference between genders is narrower in the subsample. Again, these features reflect the labor market participation restriction on the subsample. The subsample over represents non-black people compared to the full sample. The birth rate is higher for the subsample. This is because the full sample considers not only married people and divorcees but also singles who are less likely to give birth. As I restrict the sample to have at most three children, the statistics for number of children are not perfectly comparable to that of the full sample.

Obviously, the labor participation restriction implies that the participation rate is higher. It turns out that despite the higher participation rate, females work less than in the full sample. Since the subsample excludes single females who would work full time, this is expected. Accordingly, as females work less in the subsample, they earn less compared to the wage in the full sample. This likely reflects the effect of accumulated human capital on wages. Despite some discrepancies from the full sample, the general observations about the full sample still apply in the subsample. For example, the labor market participation rate for males dropped by 6 percentage points and that for females increased by 16 percentage points during the study period. Also the labor supply of females has almost doubled and the education level for both genders has increased on average by 1.46 years.

4.2 Model

Several ways to model the decision making process in a household have been proposed. The most traditional one is the unitary approach in which a household is viewed as a single decision maker and the utilities of each members of the household are ignored. To model a more realistic allocation within a household, the cooperative approach relying on axiomatic bargaining is proposed by Manser and Brown [1980] and McElroy and Horney [1981]. Also the non-cooperative approach has been adopted, for example in Lundberg and Pollak [1994], in which each member of a household tries to maximize his or her utility considering the other member's action. Finally the collective approach has been developed since Chiappori [1988] where only Pareto optimality is assumed.[2] These static household behavior models are extended to a dynamic setting in various papers. Lich-Tyler [2001] studies a multi-period household bargaining problem and Echevarria and Merlo [1999] explored the educational gender differences in the framework of a dynamic household bargaining. In a dynamic non-cooperative setting, Brown and Flinn [2006] examine the investments in children and marital status.

In this paper the collective approach assuming Pareto optimality is utilized. As is well known, a Pareto optimal solution can be obtained through the maximization of the social welfare function. The social welfare function is a weighted sum of each house member's utility, which are a husband and a wife in the model.[3] Then the problem becomes a single agent problem in which the agent is a household that solves the following multi-period problem, under the budget constraints and time constraints:

$$\max \quad \sum_{t}^{T} \beta^{t-1} \{ \boldsymbol{\delta}_{ft} u_{ft} + \boldsymbol{\delta}_{mt} u_{mt} \} \tag{4.1}$$

where f refers to a wife (female), m refers to a husband (male), β represents the time

[2] For a survey on these three different approaches, see Vermeulen [2002].

[3] Ideally the weight should reflect some sort of bargaining power through the observables of each member. Hence, the subscript t is used to denote the possibility that the weight can be a function of time varying variables such as wages of each member. If the weights become just a fixed number that either can be estimated or is assigned by a researcher, then the model follows the unitary household utility maximization with different individual utility function. This is the approach used in the estimation here, and hence the estimated Pareto weights are not time varying and do not depend on the observable characteristics of the members of the household. If there will not be any variables that are shared in each member's utility function, then the model resembles that of Samuelson [1956].

Table 4.1: Choice Set

Choice	k_1	k_2	k_3	k_4	k_5	k_6	k_7	k_8	k_9	k_{10}	k_{11}	k_{12}
d_f	1	1	0	0	1	1	0	0	1	1	0	0
d_m	1	0	1	0	1	0	1	0	1	0	1	0
m	1	1	1	1	1	1	1	1	0	0	0	0
b	1	1	1	1	0	0	0	0	0	0	0	0

d_f:the indicator that the wife works, d_m:the indicator that the husband works, m:the indicator that the couple stays married, b:the indicator that a child is born

preference and $\boldsymbol{\delta}$ is the weight. I assume the full commitment of each spouse or the full-efficiency framework.[4] The arguments of the utility functions and the constraints will be discussed later.

At the beginning of each period the household observes the state variables and picks one of the choices that would yield the maximum for the lifetime social welfare function. The choice sets are introduced the Table 4.1. Each choice is composed of the labor supply decision of the wife and husband, the childbirth decision and the choice of staying married. I abuse the notation slightly: the choice $k_s = 1$ is interpreted as an indicator that the action k_s is chosen. The actions are exclusive so $\sum_{s=1}^{12} k_s = 1$. For this choice set, note that the divorce decision is neither unilateral nor bilateral in this setting. Rather a divorce occurs when the value of lifetime social welfare function evaluated at $m = 1$ is the greatest among the alternatives. This means that the divorce decision considers both member's utility level when the divorce occurs. This divorce decision process is a compromise between "bilateral" and "unilateral" assumptions. The household maximizes the following lifetime objective function:

$$\max \sum_{t}^{T} \beta^{t-1} \sum_{s=1}^{12} k_s(\boldsymbol{\delta}_{ft} u_{fst} + \boldsymbol{\delta}_{mt} u_{mk_s t} + \varepsilon_{k_s t}) \tag{4.2}$$

where $\varepsilon_{k_s t}$ is the idiosyncratic term associated with the choice. Once divorce has occurred, the problem becomes a single agent problem. Remarriage is not allowed and females cannot bear a child while they are single in the model; hence, an individual who went through divorce in the past has a choice of labor supply only.[5] Denote kk_1 the indicator of working and kk_2 that of not working. Then the individual i who is

[4]For the role of full-efficiency or partial-efficiency in the dynamic collective approach, see Mazzocco [2007].

[5]Since I do not observe the characteristics and history of potential spouses for remarriage, I do not model the marriage decision and consequently cannot permit remarriage.

divorced maximizes a lifetime utility stream of the following form:

$$\max \sum_{t}^{T} \beta^{t-1} \sum_{s=1}^{2} kk_s(u_{ikk_st} + \varepsilon_{kk_st}). \tag{4.3}$$

The idiosyncratic terms, ε_{k_st} and ε_{kk_st}, are independently and identically distributed over individuals, periods and actions.

4.2.1 Wage equation and children production functions

First I investigate the wage equation that is used throughout the paper. Wage is determined by past labor supply decisions and personal characteristics:

$$w_{it} = \mu_i \lambda_t \exp(z_{it}\beta_1^w + \vec{d}_{it}\beta_2^w + \vec{h}_{it}\beta_3^w) \exp(\epsilon_{it}) \tag{4.4}$$

where μ is the individual specific productivity measured by individual fixed effect, λ is the time fixed effect, and z is the personal characteristics consisting of age, education level and gender.[6] A history of discrete labor market participation, $\vec{d}_{it} = \{d_{ir}\}_{r=t-s}^{t-1}$, and that of continuous hours worked, $\vec{h}_{it} = \{h_{ir}\}_{r=t-s}^{t-1}$, are included in the wage equation. ϵ is an error term associated with reported wage. I assume that the error term is independent of the independent variables in the wage equation, labor participation decisions and over the individuals. The remedy for the self-selection problem is not needed under this assumption. It is also assumed that the structure of the wage equation is common knowledge and each grown up individual observes the determinants, including his own productivity and time fixed effect.

There exists some relation between the labor market outcome of the children and the behavior of parents. This relation is represented in "children production functions" in which the individual specific productivity and eduction level of children are dependent variables. In these functions the parental behavior affects the outcome of the children through time investment in the children and family dissolution variables. That is, what parents have done affects the individual specific productivity and the education level of the children through how much time their parents spent with the children and whether the family was dissolved during the childhood of the children.[7]

[6] In practice, the wage equation is estimated by gender so z does not contain a gender variable.

[7] Parental choice may also influence hours worked and labor market participation of children in the future, but due to limits inherent in the data set, I ignore this possibility.

The individual specific productivity of a child is

$$\ln \mu_{i''} = \alpha_{\mu 0} + \sum_{i \in \{f,m\}} (\alpha^i_{\mu 1} Q_i + \alpha^i_{\mu 2} Q_i^2 + \alpha^i_{\mu 3} \mu_i + \alpha^i_{\mu 4} edu_i) + \alpha_{\mu 5} B + e^{\mu}_{i''} \tag{4.5}$$

where the superscript $''$ refers to the child, Q is the time invested to the child, B is the number of years that the child is exposed to family dissolution and e is the error term. The education level of the children is

$$edu_{i''} = \alpha_{e0} + \sum_{i \in \{f,m\}} (\alpha^i_{e1} Q_i + \alpha^i_{e2} Q_i^2 + \alpha^i_{e3} \mu_i + \alpha^i_{e4} edu_i) + \alpha_{e5} B + e^{edu}_{i''}. \tag{4.6}$$

The measure of Q for each child is the average yearly time investment in each child during the age 1 to s.[8] Let L_{it} be the time spent with all of the children at a given year t:

$$L_{it} = \kappa \sqrt{N_{it}} (1 - h_{it}) \tag{4.7}$$

where h_{it} is the amount of hours devoted to the labor market and N_{it} is the number of children. Then Q_i for one of i's children is defined as;

$$Q_i = \frac{1}{s} \sum_{t=1}^{s} \frac{L_{it}}{N_{it}}. \tag{4.8}$$

The above specifications are used to conjecture the individual specific productivity and the education level of the children in the following sections.[9]

4.2.2 Parametrization of utility functions

This section introduces the functional form of the utility function of each household member. Let denote u_{ikt} be the utility level that a member $i \in \{f, m\}$ gets when his or her choice in period t is $k \in \{k_1, k_2, \ldots, k_{12}, kk_1, kk_2\}$. This utility level is composed of five sub-utilities introduced below. To emphasize that each of these sub-utilities

[8] In practice, s is set to 10. For the purpose of obtaining moment conditions later on, it is assumed that in the year when a child is newly born the existing children do not get any time investment from parents. Also the new born child does not get any either, based on the argument that the child is not greatly affected by the care from the parents for the first 12 months.

[9] Since the parameter κ is not observable, it should be noted that the estimates of $\{\alpha^i_{\mu 1}, \alpha^i_{e1}, \alpha^i_{\mu 2}, \alpha^i_{e2}\}$ involve the value of κ. However, κ will be identified once the utility parameters are estimated.

are choice dependent, the choice related variables are bolded. Also the superscript $i = \{f, m\}$ is used for the parameters that are gender specific.

1. Utility from labor market participation:

$$u_{ft}^{p} = \gamma_p^f \mathbf{d}_{ft} z_{ft}$$

   where z_{ft} is the characteristics of a female.

2. Utility from leisure:
   An individual gets utility from his or her private leisure. The amount of private leisure is not observable since they devote some time to their children. Hence I model private leisure, l_{it} as follows:

$$h_{it} + l_{it} + L_{it} = 1$$

   where L_{it} is the time investment in the children introduced earlier.[10] These variables are normalized so that the total time available is a unit. Then the specification is:

$$u_{it}^{l} = \gamma_{l1}^{i} \mathbf{l}_{it} z_{it} + \gamma_{l2}^{i} \mathbf{l}_{it}^{2} + \gamma_{l3}^{i} \mathbf{m}_t \mathbf{l}_{it} \mathbf{l}_{i't}$$

   where i' refers to the other member ($i' = f$ if $i = m$ and vice versa). Note that whenever $d = 0$, $l = 1$ and $h = 0$. The third term of the right hand side examines the substitute or complement effect of partner's leisure.

3. Utility from leisure with a birth effect
   When a child is newly born, the utility from leisure is assumed to be affected in the following way;

$$u_{it}^{b} = \gamma_b^i \mathbf{b}_t \mathbf{m}_t \mathbf{l}_{it} z_{it}.$$

[10]In the actual estimation, I adopt the specification of $h_{mt} + l_{mt} = 1$. That is, while females spend time with the children, males do not distinguish private leisure and time devoted to the children. This specification mostly reflects the data. As discussed later, the proxy for paternal time spent with children does not show the results correlated either with the individual specific productivity or with the education level of the children. Therefore, I assert that the presence of a father itself affects the labor market outcome of the children, which is captured in the variable B, not the paternal time spent with the children. Since the paternal time spent with children does not affect the utility from the second generation, there is no trade-off with private leisure for males; that is, males will choose not to spend any time with their children if the variable of paternal time is considered.

4. Utility from consumption

   It is assumed that there is no saving or borrowing over the periods. Hence, all earned income is consumed in a given year. Also it is assumed that if married, female gets a share, δ_c, of pooled income and male gets the rest for his consumption. The parameter π captures the cost of children as a function of number of children. Then the utility from consumption becomes;

$$u_{it}^c = \gamma_{c1}^i c_{it}(\mathbf{b}_t, \mathbf{h}_{it}, \mathbf{m}_t, \mathbf{h}_{i't}) + \gamma_{c2}^i c_{it}(\mathbf{b}_t, \mathbf{h}_{it}, \mathbf{m}_t, \mathbf{h}_{i't})^2$$

   where

$$c_{it} = \begin{cases} \delta_c(1 - \pi\sqrt{N_{i,t-1} + \mathbf{b}_t})(w_{it}\mathbf{h}_{it} + \mathbf{m}_t w_{i't}\mathbf{h}_{i't}) & \text{if } i = f \\ (1 - \delta_c)(1 - \pi\sqrt{N_{i,t-1} + \mathbf{b}_t})(w_{it}\mathbf{h}_{it} + \mathbf{m}_t w_{i't}\mathbf{h}_{i't}) & \text{if } i = m. \end{cases}$$

5. Utility from offspring

   Part of utility is from the expected labor market outcome of children. This source of utility is only influenced by actions parents take before their children enter the labor market. Recall that the wage equation is a function of the characteristic z that contains age, education level and individual specific productivity and labor supply history. Parents use the information in the wage equation to infer the future outcome of their children. More precisely, the arguments through which the parents can affect the wage outcome of children enter the parents' utility:

$$u_{iti''}^o = g(\mu_{iti''}, edu_{iti''})$$

   where $i'' \in \{1, 2, \ldots, N_i\}$ is a child index among N_{it} children who have not entered the labor market.[11] Since utility from offspring enters in the presence of the non-grown up child, it is clear that getting the value for the individual specific productivity and the education level when the child actually enters the labor market is impossible. Hence, parents form expectations of these variables, which are affected by their own actions. To find this, I borrow the results of children production functions that are presented in the later section. Recall that the individual specific productivity and the level of education can be well

[11] To be precise, the age when a child enters the labor market should be affected by the parents. However I assume that this age is deterministic outcome of the education level. Hence, by controlling the education level, it implicitly takes care of the parental effect to the age at which the child enters the labor market.

predicted by the regressors of time investment of the parents and being from a broken family along with the individual specific productivity and the education level of each parent. I nonparametrically predict the amount of time investment and the number of years that the child might be exposed to the disrupted family so that I can predict the individual specific productivity and the education level of the child. By adopting the linear specification, the utility from offspring is:

$$u^o_{iti''} = \gamma_{sg1}\widetilde{\ln\mu}^o_{iti''} + \gamma_{sg2}\widetilde{edu}^o_{iti''}.$$

The altruistic factor, ζ, is considered in the following way: [12]

$$u^o_{it} = \zeta \sum_{i''=1}^{N_{it}} u^o_{iti''}.$$

Given the above utility components, the per period utility of i is:

$$u_{it} = u^p_{it} + u^l_{it} + u^b_{it} + u^c_{it} + u^o_{it}.$$

4.3 Estimation

4.3.1 Moment conditions

The moment conditions employed in this paper come from two sources: (1) the alternative representation of the conditional valuation function difference and (2) the Euler equation. The first source heavily depends on the property of finite state dependence. A pair of actions exhibits finite state dependence if there exists a sequence of actions for some periods (say ρ), $\{k_s\}^{\rho}_{s=t+1}$, such that the state at $t+\rho+1$ is the same for both of actions in the pair taken at t.[13] This finite state dependence property is used in several papers including Altug and Miller [1998], Gayle and Miller [2006] and Gayle and Golan [2008]. The model can be identified as long as each action is involved in at least one of the pairs exhibiting finite state dependence or in any of Euler equations.

[12]Note that the identification of ζ is limited. Instead $\zeta\gamma_{sg1}$ and $\zeta\gamma_{sg2}$ are estimated.

[13]For a formal definition of finite state dependence, refer to Definition 1 in Arcidiacono and Miller [2008].

In the framework developed in this paper, the choice pairs exhibiting finite state dependence are P1: (k_1, k_3), P2: (k_5, k_6) and P3: (k_7, k_8) when the couple stays married and P4: (kk_1, kk_2) for the divorced males and P5: (kk_1, kk_2) for the divorced females with $\rho = 2$.[14] Table 4.2 provides the sequence of actions needed to achieve finite state dependence for these pairs of actions at t. If multiple paths are available for the same pair of actions, I chose the pair that occurs more frequently. It should be noted that these are not the only available pairs. For example, if a household follows a sequence of actions, namely k_5 at $t+1$ and $t+2$, then the pair of action taken at t, (k_2, k_3) will generate the same set of state variables at $t+3$. However this pair is not used in estimation due to the small number of incidents of such paths in the data. The previously mentioned pairs, P1$\sim$ P5, are those whose designated set of actions occur frequently in data. Also note that a pair involving both "stay married ($m = 1$)" and "divorced ($m = 0$)" is not employed since finite state dependence cannot be established for the pair.[15] With the paths exhibiting finite state dependence, I can get the following moment conditions from the conditional valuation function differences and the first order condition with respect to hours worked, a continuous variable:

Proposition 1. *Let $p_{k_1}(H_t)$ be the conditional choice probability of action k_s given the state H_t, namely, $p_{k_s}(H_t) = E(k_s^* = 1|H_t)$ and define $H_{k_st}^{(q)}$ to be the set of state variables at $t+q$ when the decision maker chooses action k_s at t and the artificial paths, $\{k^z\}_{z=1}^q$, from $t+1$ to $t+q$ to achieve finite state dependence. Also let the action pair k_s and $k_{s'}$ to represent one of pairs in Table 4.2 and $k_h \in \{k_1, k_5, k_6, kk_1\}$ for $i = f$ and $k_h \in \{k_1, k_3, k_5, k_7, kk_1\}$ for $i = m$ and $h \in \{s, s'\}$. Then the first set of moment conditions is*

$$\ln \frac{p_{k_s}(H_t)}{p_{k_{s'}}(H_t)} = u_{k_st} - u_{k_{s'}t} + E\sum_{z=1}^{q} \beta^z \left[u_{k^z}(H_{k_st}^{(z)}) - u_{k^{z'}}(H_{k_st}^{(z)}) + \ln \frac{p_{k^{z'}}(H_{k_{s'}t}^{(z)})}{p_{k^z}(H_{k_st}^{(z)})} \right] \tag{4.9}$$

[14] To be exact, pair P5 does not exactly satisfy finite state dependence since the time investment input of the mother cannot be the same after ρ periods for those children who are less than or equal to 10 years old at t. I could either exclude P5 from the set of moment conditions or using it without employing people with children less than or equal to 10 years old at t. I choose the latter since it allows me to use a bigger sample.

[15] Since the children production functions are functions of the number of years of family disruption, having divorced this year versus staying married this year cannot generate the same prediction on children production functions unless remarrying the same (or almost same) person is possible. Since remarriage itself is not allowed in the model, it is not possible to construct such a pair.

Table 4.2: Artificial Paths

	Households						Divorcees Males		Divorcees Females	
	P1		P2		P3		P4		P5	
t	k_1	k_3	k_5	k_6	k_7	k_8	kk_1	kk_2	kk_1	kk_2
$t+1$	k_5	k_5	k_5	k_5	k_8	k_8	kk_2	kk_2	kk_1	kk_1
$t+2$	k_5	k_5	k_5	k_5	k_8	k_8	kk_2	kk_2	kk_1	kk_1

and the second set of moment condition is

$$\frac{\partial V_{k_s t}}{\partial h_{it}} = \frac{\partial u_{k_s t}}{\partial h_{it}} + E_t \sum_{z=1}^{q} \beta^z \left(\frac{\partial u_{k^z}(H_{k_s t}^{(z)})}{\partial h_{it}} - \frac{\partial p_{k^z}(H_{k_s t}^{(z)})}{p_{k^z}(H_{t,k_s}^{(z)}) \partial h_{it}} \right). \tag{4.10}$$

See the proof in Appendix.

4.3.2 First stage - wage equation and children production function

Equation 4.4 is estimated using the panel data employing the first differencing method. Taking logarithms on the equation and differencing between two adjacent periods yields

$$\Delta \ln w_{it} = \Delta \ln \lambda_t + z_{it}\beta_1^w + \vec{d}_{it}\beta_2^w + \vec{h}_{it}\beta_3^w + \Delta\epsilon_{it}. \tag{4.11}$$

Let $X_{it} \equiv \Delta\{z_{it}, \Delta\vec{d}_{it}, \Delta\vec{h}_{it}\}$, $Y_{it} \equiv \Delta \ln w_{it}$ and $\boldsymbol{\beta}^w \equiv \{\beta_1^w, \beta_2^w, \beta_3^w, \{\Delta \ln \lambda_r\}_{r=2}^T\}$. Further, $X_i \equiv \{X_{ir}\}_{r=2}^T$ and $Y_i \equiv \{Y_{ir}\}_{r=2}^T$. Then equation 4.11 can be restated as

$$Y_{it} = X_{it}\boldsymbol{\beta}^w + \Delta\epsilon_{it}.$$

$\boldsymbol{\beta}^w$ is estimated as following;

$$\tilde{\boldsymbol{\beta}}^w = (N^{-1}\sum_{i=1}^{N} X_i'\tilde{W}_i^{-1}X_i)^{-1}(N^{-1}\sum_{i=1}^{N} X_i'\tilde{W}_i^{-1}Y_i)$$

where $\tilde{W}_i$ is a consistent estimator of[16]

$$W_i \equiv E\{(Y_i - X_i\boldsymbol{\beta}^w)(Y_i - X_i\boldsymbol{\beta}^w)'|X_i\}.$$

[16] A vector $\{\Delta\epsilon_{it}\}_{t=1}^T$ is assumed to be homoscedastic. Hence, W_i is independent of i. The estimation of $\tilde{W}_i$ is done by using the average of $\tilde{W}_i$ over individuals.

It is assumed that $E(\Delta\epsilon_{it}|X_i = 0)$ so that the above estimator achieves the minimum asymptotic covariance among the class of GMM estimators.

The children production functions cannot employ the panel data structure since the variables in the production functions are time invariant. Equation 4.5 and equation 4.6 are estimated by OLS under the assumption that the error terms e^{μ} and e^{edu} are independent of the covariant used in each production function.[17]

4.3.3 First stage - nonparametric estimation

Once the estimation of the wage equation and the production functions for children is done, the next stage of the estimation is to recover nonparametrically the conditional choice probabilities, the time investment measure for the children and the number of years the children are exposed to a disrupted family. These nonparametric estimates are obtained for the period from t to $t+q$ using the kernel estimator:

$$\begin{aligned} \tilde{p}_{k_s}(H_{it}) &= \frac{\sum_{j=1}^{N}\sum_{r=1}^{T} k_{s,jr} K(c(H_{it}-H_{jr}))}{\sum_{j=1}^{N}\sum_{r=1}^{T} K(c(H_{it}-H_{jr}))} \\ \tilde{p}_{k_a}(H_{k_s it}^{(d)}) &= \frac{\sum_{j=1}^{N}\sum_{r=1}^{T} I_{k_s jr}^{(d)} k_{a,jr} K(c(H_{k_s it}^{(d)}-H_{k_s jr}^{(d)}))}{\sum_{j=1}^{N}\sum_{r=1}^{T} I_{k_s jr}^{(d)} K(c(H_{k_s it}^{(d)}-H_{k_s jr}^{(d)})))} \end{aligned} \tag{4.12}$$

$$\begin{aligned} \tilde{Q}_{k_s i''}(H_{it}) &= \frac{\sum_{j=1}^{N}\sum_{r=1}^{T}\sum_{j''} Q_{j''} I_{j''r>10} k_{s,jr} K(c(H_{it}-H_{jr}))}{\sum_{j=1}^{N}\sum_{r=1}^{T}\sum_{j''} I_{j''r>10} k_{s,jr} K(c(H_{it}-H_{jr}))} \\ \tilde{Q}_{k_a i''}(H_{k_s it}^{(d)}) &= \frac{\sum_{j=1}^{N}\sum_{r=1}^{T}\sum_{j''} Q_{j''} I_{j''r>10} I_{k_s jr}^{(d)} k_{a,jr} K(c(H_{k_s it}^{(d)}-H_{k_s jr}^{(d)}))}{\sum_{j=1}^{N}\sum_{r=1}^{T}\sum_{j''} I_{k_s jr}^{(d)} I_{j''r>10} I_{k_s jr}^{(d)} k_{a,jr} K(c(H_{k_s it}^{(d)}-H_{k_s jr}^{(d)})))} \end{aligned} \tag{4.13}$$

$$\begin{aligned} \tilde{B}_{k_s i''}(H_{it}) &= \frac{\sum_{j=1}^{N}\sum_{r=1}^{T}\sum_{j''} B_{j''} D_{j''} k_{s,jr} K(c(H_{it}-H_{jr}))}{\sum_{j=1}^{N}\sum_{r=1}^{T}\sum_{j''} D_{j''} k_{s,jr} K(c(H_{it}-H_{jr}))} \\ \tilde{B}_{k_a i''}(H_{k_s it}^{(d)}) &= \frac{\sum_{j=1}^{N}\sum_{r=1}^{T}\sum_{j''} B_{j''} D_{j''} I_{k_s jr}^{(d)} k_{a,jr} K(c(H_{k_s it}^{(d)}-H_{k_s jr}^{(d)}))}{\sum_{j=1}^{N}\sum_{r=1}^{T}\sum_{j''} I_{k_s jr}^{(d)} D_{j''} I_{k_s jr}^{(d)} k_{a,jr} K(c(H_{k_s it}^{(d)}-H_{k_s jr}^{(d)})))} \end{aligned} \tag{4.14}$$

where $I_{k_s jr}^{(d)} \equiv k_{sjr-d} \prod_{l=1}^{d-1} k_{mr-l}^{(d)}$ indicates whether j has followed the path designated to exhibit finite state dependence, $I_{j''r>10}$ indicates if the age of j's child, j'', is over 10 or not and $c \equiv h^{-1}$ with an optimal bandwidth, h, chosen by the criterion of integrated square error.[18] The index i should be understood as either a household or an individual depending on the action set $\{k\}$ or $\{kk\}$. The subscript i'' helps to

[17] GLS is also tried to estimate the production functions. The results are not that different from what I have from OLS estimation.

[18] Since there are many ties in data, the usual cross-validation approach based on ISE to pick the optimal bandwidth does not work properly. Hence, I adopt the method suggested in Zychaluk and Patil [2008].

distinguish the expected child investment, Q, and the length of being exposed in a broken family, B, for each child. Since I do not impose the restriction of $Cov(Q) = 0$, I directly estimate $\tilde{Q}^2$ instead of squaring $\tilde{Q}$. The kernel estimators for Q^2 are the same as those for Q in equation 4.13 except replacing Q^2 for Q. The estimated B averages (with weights) over those children whose parents actually have divorced or will divorce. They can be selected by using indicator $D_{j''}$ which gives value one if parents have divorced during j'''s childhood. Note that I do not need to estimate B for already divorced people since then it is no longer random but deterministic.[19] The means of each nonparametric estimate are provided in Table 4.8, Table 4.9, Table 4.10 and Table 4.11.

4.3.4 Second stage - utility parameters estimation

The two sets of moment conditions from Proposition 1, $m1_{Pit}$ and $m2_{k_s it}$, are rewritten below:

$$
\begin{aligned}
m1_{Pit}(\theta_u, \tilde{\theta}_w, \tilde{\theta}_q, \tilde{\psi}) &= \ln \frac{p_{k_s}(H_t)}{p_{k_{s'}}(H_t)} \\
&- \left[u_{k_s t} - u_{k_{s'} t} + \sum_{z=1}^{q} \beta^z [u_{k^z}(H^{(z)}_{k_s t}) - u_{k^{z'}}(H^{(z)}_{k_s t}) + \ln \frac{p_{k^{z'}}(H^{(z)}_{k_{s'} t})}{p_{k^z}(H^{(z)}_{k_s t})}] \right]
\end{aligned}
$$

where P takes one of $P1 \sim P5$ and

$$
m2_{k_s it}(\theta_u, \tilde{\theta}_w, \tilde{\theta}_q, \tilde{\psi}) = \frac{\partial V_{k_s t}}{\partial h_{it}} - \left[\frac{\partial u_{k_s t}}{\partial h_{it}} + \sum_{s=1}^{z} \beta^s \left(\frac{\partial u_{k^z}(H^{(z)}_{k_s t})}{\partial h_{it}} - \frac{\partial p_{k^z}(H^{(z)}_{k_s t})}{p_{k^z}(H^{(z)}_{k_s t}) \partial h_{it}} \right) \right]
$$

where k_s is one of k_1,k_3,k_5,k_6,k_7 and kk_1.[20] The argument θ_w is the vector of parameters in the wage equation and θ_q is those in the specification of children production functions in equation 4.5 and equation 4.6. The vector ψ contains all nonparametrically estimated entities of conditional choice probabilities, Q, Q^2 and B. These arguments are tilted to indicate that they are pre-estimated in previous stages. The argument θ_u is the vector of parameters of each utility function used in the moment conditions. Note that not all of the elements in θ_u are structural parameters at this

[19] For example, if one gets divorced when the child is 5 then B for that child is $13(= 18-5)$ years.

[20] In $P1 \sim P3$, i should be understood as a household rather than an individual. In actual estimation, the time preference parameter, β, is set to 0.9.

stage. However I introduce the functional restriction between θ_u and the structural parameters θ_{us} of $f(\theta_u, \theta_{us}) = 0$.

Define $M_{it}(\theta_u, \tilde{\theta}_w, \tilde{\theta}_q, \tilde{\psi}) \equiv [m1_{Pnt}(\theta_u, \tilde{\theta}_w, \tilde{\theta}_q, \tilde{\psi}), m2_{k_s nt}(\theta_u, \tilde{\theta}_w, \tilde{\theta}_q, \tilde{\psi})]'$ and $M_i(\cdot) \equiv [M_{it}(\cdot)', \cdots, M_{iT}(\cdot)']'$.[21] Also define $\Omega_{it} \equiv E_t[M_{it}(\theta_u, \tilde{\theta}_w, \tilde{\theta}_q, \tilde{\psi}) M_{it}(\theta_u, \tilde{\theta}_w, \tilde{\theta}_q, \tilde{\psi})']$ and let Ω_i be a T by T matrix for i whose block diagonal elements are $\{\Omega_{it}\}_t^T$ and off-diagonal elements are zero. The initial consistent estimates of utility parameters, $\tilde{\theta}_{u^1}$, are estimated by

$$\tilde{\theta}_{u^1} \equiv \underset{\theta_u}{\operatorname{argmin}} \frac{1}{N} \sum_{i=1}^{N} M_i(\theta_u, \tilde{\theta}_w, \tilde{\theta}_q, \tilde{\psi})' M_i(\theta_u, \tilde{\theta}_w, \tilde{\theta}_q, \tilde{\psi}).$$

Having $\tilde{\theta}_{u^1}$ on hand, Ω_{it} is estimated nonparametrically using $M_{it}(\tilde{\theta_{u^1}}, \tilde{\theta}_w, \tilde{\theta}_q, \tilde{\psi})$.[22] Then the optimal estimates of utility parameters, $\tilde{\theta}_{u^2}$, are estimated by

$$\tilde{\theta}_{u^2} \equiv \underset{\theta_u}{\operatorname{argmin}} \frac{1}{N} \sum_{i=1}^{N} M_i(\theta_u, \tilde{\theta}_w, \tilde{\theta}_q, \tilde{\psi})' \tilde{\Omega}_i^{-1} M_i(\theta_u, \tilde{\theta}_w, \tilde{\theta}_q, \tilde{\psi}).$$

Note that the existence of first stage estimates and nonparametric estimates requires the correction for the asymptotic variance of $\tilde{\theta}_{u^2}$ following Newey and McFadden [1994].

Recall that θ_u is a vector of reduced form parameters. To estimate the structural parameters, the asymptotic least square estimator is employed. Specifically, given the relation $f(\theta_u, \theta_{us}) = 0$, θ_{us} is estimated by[23]

$$\tilde{\theta}_{us} \equiv \underset{\theta_{us}}{\operatorname{argmin}} f'(\tilde{\theta}_{u^2}, \theta_{us}) \tilde{S} f(\tilde{\theta}_{u^2}, \theta_{us})$$

where $\tilde{S}$ is an estimated weighting matrix. According to Kodde, Palm, and Pfann

[21] The length of M_{it} is not the same for all i. For households, the length can range from zero to five. For divorcees, it can be up to two depending on the number of the moment conditions used.

[22] To ensure that the estimate of Ω_{it} is positive semi-definite, the set that the estimate is weighted averaged over is chosen by the size of the matrix. For example, suppose the size of Ω_{nt} is r x r and $\{N_s\}_{s=1}^{0.5*r*(r+1)}$ is the sequence of number of incidents of elements in matrix Ω_{nt} obtained from data. Then using the set of data which corresponds to min$\{N_s\}$ in a nonparametric estimator makes the final estimate of the matrix positive semi-definite.

[23] To be exact the relation is $f(\theta_{us}) = \theta_u$ and this reduces to the minimum distance estimator.

[1990], the following choice is the optimal weighting matrix;

$$\tilde{S} = (\tilde{Q}V\tilde{Q}')^{-1}$$

where $\tilde{Q} \equiv \partial f(\tilde{\theta}_u, \theta_{us})/\partial\theta_u$ and V is the asymptotic variance matrix of $\tilde{\theta}_u$. When $\tilde{S}$ is used as weighting matrix, the asymptotic distribution of $\tilde{\theta}_{us}$ is

$$\sqrt{N}(\tilde{\theta}_{us} - \tilde{\theta}_{us_0}) \underset{a}{\sim} \boldsymbol{N}(0, (F'(Q\Omega Q')^{-1}F)^{-1})$$

where $F = \partial f(\theta_u, \theta_{us})/\partial\theta_u$.

4.4 Identification

The identification of the individual preference parameters and the household parameters such as the Pareto weights is built on the assumption that individual preferences are the same before and after divorce. Variance in choices made when agents are single versus when they are married identifies the parameters describing the social welfare problem solved within a married household. For example, suppose a male and a female are married, and both work more than full time. Then, this couple gets divorced. Suppose then that the male works part time while the woman continues to work more than full time. If the wage rate is similar, this indicates that the woman prefers consumption while the man prefers leisure. Since both worked more than full time when they were married, this implies that when the "household" makes the labor leisure decision for both agents it puts more weight on the woman's preference for consumption than on the man's preference for leisure. This example shows that the difference in behavior of the couple as a married pair versus as divorcees helps identify the Pareto weights within the household.

This identification strategy of using singles is similar to some strategies proposed in the literature on household preferences. For example, McElroy [1990] suggests using singles data to determine threat points in a Nash bargaining model while Barmby and Smith [2001], Vermeulen et al. [2006] and Browning, Chiappori, and Lewbel [2008] use the approach to identify the collective model of households.

This approach is not innocuous in two ways. First, it is questionable that the preferences of single individuals are the same as those of married people. It could be the case that the singles behave significantly different from married people. However, note that the single people used in this paper are those who are divorced not those who are never married. Since these singles are in conditions similar to those facing married people, such as having children, it is more reasonable to use them than to assert that singles who are looking for a life partner for the first time have the same preferences as married people. Additionally, by explicitly modeling the distribution of income within a family and the different leisure opportunities available to married couples, I directly account for how preferences over work and income can differ between the two populations. Only the deep preference parameters are assumed to be invariant. Finally, since I use panel data in which the same individuals can be divorcees while they were married before, I do not get the preferences of singles and married persons with totally independent samples.[24]

The second concern about using this identification strategy, as pointed out in Chiappori [1991], is that it is not entirely clear how the cardinality of the singles' utility can be determined when the household's utility is considered. Regarding this concern, it is worth revisiting how the choice specific error terms are structured. The error terms in equations 4.2 and 4.3 are independently and identically distributed over households and divorcees. This error term structure effectively introduces a normalization on cardinality and pins down the identification of the *level* of each spouse's Pareto weight. Since the normalization of the variance of the choice specific error terms implies a specific level for the Pareto weights, I do not need to impose additional normalizations on the weights, such as assuming they sum to one.

This identification procedure allows us to relax some of limits in the identification of the collective model pointed out, for example, in Chiappori and Ivar [2009]. First, the Pareto weights are identified even though, in other settings, it is argued that the identification is limited if the weights are constant. Second, the model can be identified without restricting preferences to be egoistic or caring, both of which are needed when household behavior is modeled in a collective approach without resorting to singles behavior.

[24]Additionally, the preference of individuals and the Pareto weights are estimated jointly using a minimum distance estimator. This results in an efficiency gain over the case where the preference of singles are just plugged into the social welfare function.

4.5 Empirical Results

Wage Equation

The wage equation with two periods of labor market supply history is estimated and Table 4.6 summarizes the results. All variables are significant at the 5% level for both genders. The results show that more recent hours worked have bigger marginal effects on wage than less recent ones. The effect of last year's hours worked for females is more than twice that of two years ago and also bigger than that of males. The negative coefficients on participation variables imply that there is a threshold in hours worked to have positive returns on wage. The quadratic age profile is observed and a higher education level fixing the age or being older fixing the education level has a positive marginal effect on wage.

Children Production Functions

Table 4.7 provides the results of children production function regressions.[25] The maternal time investment and the parents' individual specific productivity have significant effects on children's individual specific productivity and education level. It is useful to see how the change of maternal time investment affects the outcomes of production functions. For example, consider a mother who has one child and does not participate in the labor market. If instead she decides to work full time for the first 10 years following the birth of the child, then the change of the individual specific productivity of her child would be -0.1915 while the change in the education level the child would attain would be -0.0694.[26] It appears that less maternal time investment negatively affects the production functions of the only child. Now consider a female who has three children and does not work. If I assume that she works full time for 10 years following the birth of the last child, then the change in the individual specific productivity of the last child would be 0.0174 while that of the education level would be -0.2717. This can be interpreted as the labor market participation of mother having a positive effect on the individual specific productivity of the child, possibly by

[25]A sub-sample is used to obtain these results; for someone to be used in the regression, it is necessary that a couple provides the labor market data of themselves during their children's childhood and that they have grown up children who have participated in the labor market. This requires the member of the panel to be in the survey for a long period and, hence, only a sub-sample can be used.

[26]Both the linear and quadratic terms of maternal time investment in each child are used to infer these numbers although the quadratic term is not significant in the children production function for education level.

providing a role model of a working female, while the decrease in the time investment in the child may harm the final level of education for the child. These results suggest that I cannot draw a simple relationship between maternal time investment and the outcome of children without considering the number of siblings.

Figure 4.1 is provided to further aid the understanding of how maternal time investment affects the individual specific productivity of a child. The dotted line represents the case of an only child and the solid line is for the case where there are two children in the household. A monotonic relation between maternal time investment in the only child and the individual specific productivity of that child is observed. However, when there are two children, the relation is no longer monotonic. In fact, each child gets higher individual specific productivity by receiving more time investment from the mother if she provides less than "A" amount of labor supply.[27] This implies that, in the view of children's future productivity in the labor market, a mother who does not supply a great amount of labor should decrease hours worked and increase the time devoted to children. On the other hand, if the mother supplies more than "A", each child gets lower individual specific productivity as she decreases the labor supply. That is, once woman supplies fair amount of labor, being a more engaged worker benefits her children possibly by providing a role model.

Interestingly, it turns out that paternal time investment is not a significant predictor for either the individual specific productivity or the education level of the children. The fathers cannot, however, ignore the labor market outcome of their children as the decision to remain in the family or leave clearly influences the individual specific productivity and the education level of the children. In fact, the duration of the couple's separation, which is in part determined by the decisions of fathers, negatively affects the production functions.

Utility Parameters

The estimates of utility parameters are provided in Table 4.12. According to the estimate of the weight $\boldsymbol{\delta}$, wives' utility is given 42.05% weight. The estimated κ in equation 4.7 is 0.2292. This estimate implies that if there is only one child, the mother spends 22.92% of total leisure time on the child and if there are two children, $22.92 \times \sqrt{2}/2 = 16.20\%$ of total leisure time is spent per child. The cost of children, π, turns out to be 0.9781. This figure seems high and the cost of children will exceed

[27] "A" equals to 1663 hours of annual labor supply.

the current income when there is more than one child. The estimates for the female share of consumption, δ_c, is 1.2014. The estimate is outside of the reasonable range between zero and one.

Females get positive utility from participating in the labor market with more educated black women getting higher utility. This implies that women who supply labor actually tend to enjoy working or at least get some satisfaction from holding a job. This result is different from that in the previous literature on female labor supply. For example, Altug and Miller [1998], Gayle and Miller [2006] and Eckstein and Wolpin [1989] find the contrary. This contradicting result comes from the difference in the female population. The previous literature examines the behavior of married females while I analyze both married and divorced single females. The labor market participation rate is much higher for single females than married females. Therefore, given the assumption that underlying preference does not change over marital status, using single females offsets the tendency for nonparticipation of married females that has been understood to arise from a cost to participation in the labor market.

The concave functional form of utility from leisure is confirmed for both genders and most individuals exhibit positive marginal utility from leisure. The level of education has the opposite effect on leisure for each gender. More educated females enjoy leisure more, but more educated males enjoy leisure less. Being a black male brings more utility from leisure, and the level of utility from leisure increases as males age. Utility from leisure is not monotonic in age for females. For women, the marginal utility of leisure is initially decreasing in age but is then increasing. That is, young women experience declining marginal utility of leisure as they age, but after some point the pattern reverses. The model provides a measure of how the leisure of one spouse interacts with that of the other spouse through the variable $l_{nt} \times l_{n't}$ in the table. Since the coefficient on this variable is positive, members of a household enjoy each other's company.

For females, age does not play a role in determining whether the utility from leisure is affected by having another child. However, more educated women appear to enjoy leisure less when a new child is born. For males, having another newborn does not affect how the utility from leisure is determined. From the results shown for the utility from consumption, females and males do enjoy consumption although the shape of the functions differ. While males exhibit concave utility from consumption, females turn out to have an increasing and convex utility in consumption.

The children's production function positively contributes to the total utility of individuals. The individual specific productivity of children increases the level of utility, and the marginal utility of the education level of children is also positive, confirming that parents do care about the future labor market outcome of their children.

Table 4.3: Summary Statistics of Demographic Variables - Part 1[1]

	Sample size				Age				Education[2]			
Year	Male		Female		Male		Female		Male		Female	
	Full	Sub	Full	Sub	Full	Sub	Full	Sub	Full	Sub	Full	Sub
1969	1811	212	2737	218	39.7	29.8	39.2	26.2	10.99	12.41	10.84	12.35
					(12.2)	(9.6)	(12.9)	(7.7)	(3.50)	(2.59)	(2.81)	(1.97)
1970	1966	269	2911	289	39.3	29.5	39.0	26.1	11.01	12.41	10.85	12.27
					(12.7)	(9.0)	(13.4)	(7.2)	(3.46)	(2.57)	(2.80)	(2.03)
1971	2111	364	3084	376	39.2	29.0	39.1	26.1	11.02	12.34	10.85	12.29
					(13.0)	(8.5)	(13.7)	(6.8)	(3.45)	(2.52)	(2.79)	(1.99)
1972	2287	454	3268	452	39.0	29.1	39.0	26.3	11.03	12.33	10.86	12.26
					(13.3)	(8.2)	(14.1)	(6.6)	(3.42)	(2.52)	(2.79)	(1.99)
1973	2463	563	3471	558	38.8	29.2	38.9	26.4	11.04	12.27	10.88	12.26
					(13.7)	(8.0)	(14.4)	(6.6)	(3.40)	(2.50)	(2.77)	(2.03)
1974	2658	664	3676	655	38.5	29.2	38.9	26.5	11.06	12.23	10.89	12.24
					(13.9)	(7.8)	(14.7)	(6.5)	(3.36)	(2.43)	(2.75)	(1.97)
1975	2834	768	3863	755	38.5	29.4	39.0	26.8	11.97	12.99	11.56	12.77
					(14.1)	(7.7)	(14.9)	(6.5)	(3.07)	(2.37)	(2.62)	(2.06)
1976	3018	872	4059	857	38.5	29.8	39.1	27.2	12.01	12.97	11.61	12.76
					(14.3)	(7.5)	(15.1)	(6.4)	(3.02)	(2.34)	(2.59)	(2.03)
1977	3191	976	4231	973	38.6	30.0	39.3	27.5	12.03	13.00	11.65	12.80
					(14.4)	(7.5)	(15.3)	(6.4)	(2.97)	(2.31)	(2.57)	(2.05)
1978	3369	1066	4395	1057	38.9	30.5	39.6	28.0	12.05	12.96	11.69	12.82
					(14.5)	(7.5)	(15.4)	(6.5)	(2.93)	(2.30)	(2.55)	(2.04)
1979	3579	1143	4641	1149	39.0	31.1	39.6	28.5	12.09	12.92	11.75	12.80
					(14.7)	(7.5)	(15.6)	(6.5)	(2.88)	(2.31)	(2.53)	(2.05)
1980	3753	1250	4870	1252	39.2	31.5	39.7	28.9	12.13	12.91	11.81	12.81
					(14.8)	(7.6)	(15.8)	(6.5)	(2.84)	(2.26)	(2.51)	(2.03)
1981	3925	1361	5066	1359	39.6	31.9	40.0	29.4	12.16	12.92	11.85	12.83
					(14.9)	(7.7)	(15.9)	(6.6)	(2.82)	(2.23)	(2.49)	(2.00)
1982	4087	1454	5254	1469	39.9	32.4	40.4	29.8	12.21	12.94	11.91	12.84
					(15.0)	(7.7)	(16.0)	(6.7)	(2.79)	(2.18)	(2.49)	(1.97)
1983	4298	1552	5461	1583	40.1	32.9	40.7	30.3	12.31	13.05	11.98	12.95
					(15.0)	(7.9)	(16.1)	(6.8)	(2.86)	(2.29)	(2.52)	(2.05)
1984	4474	1694	5640	1693	40.4	33.3	41.0	30.8	12.33	13.05	12.04	12.97
					(15.1)	(7.9)	(16.2)	(7.0)	(2.83)	(2.29)	(2.51)	(2.04)
1985	4539	1749	5700	1759	40.5	33.9	41.2	31.3	12.73	13.47	12.37	13.31
					(15.0)	(7.9)	(16.2)	(7.0)	(2.78)	(2.28)	(2.53)	(2.08)

Continued on Next Page...

Table 4.3 – Continued

Year	Sample size				Age				Education[2]			
	Male		Female		Male		Female		Male		Female	
	Full	Sub	Full	Sub	Full	Sub	Full	Sub	Full	Sub	Full	Sub
1986	4567	1832	5702	1841	40.9	34.4	41.5	31.7	12.77	13.48	12.42	13.32
					(14.9)	(7.9)	(16.1)	(7.0)	(2.74)	(2.29)	(2.52)	(2.08)
1987	4584	1863	5741	1904	41.1	35.1	41.7	32.4	12.82	13.49	12.47	13.36
					(14.8)	(8.1)	(16.1)	(7.1)	(2.70)	(2.29)	(2.48)	(2.08)
1988	4630	1901	5770	1936	41.4	35.6	42.0	33.0	12.84	13.52	12.53	13.39
					(14.7)	(8.1)	(16.0)	(7.3)	(2.68)	(2.28)	(2.45)	(2.08)
1989	4665	1930	5809	1975	41.7	36.3	42.3	33.7	12.89	13.51	12.58	13.44
					(14.6)	(8.2)	(16.0)	(7.4)	(2.65)	(2.29)	(2.45)	(2.09)
1990	5955	1967	7463	2033	42.6	36.7	43.0	34.1	12.31	13.56	11.98	13.47
					(14.9)	(8.2)	(16.0)	(7.4)	(3.18)	(2.28)	(3.05)	(2.09)
1991	5940	2092	7430	2156	42.8	37.1	43.4	34.5	12.38	13.50	12.06	13.48
					(14.9)	(8.4)	(16.0)	(7.5)	(3.11)	(2.32)	(3.01)	(2.10)
1992	5902	2038	7499	2144	43.2	37.6	43.6	35.1	12.42	13.54	12.12	13.50
					(14.9)	(8.4)	(16.0)	(7.7)	(3.08)	(2.31)	(2.98)	(2.08)
1993	4522	1834	6003	2050	42.8	38.5	43.5	36.1	12.98	13.63	12.74	13.57
					(14.6)	(8.4)	(16.0)	(7.7)	(2.56)	(2.22)	(2.41)	(2.04)
1994	5048	1836	6556	2075	42.9	38.7	43.6	36.5	12.98	13.60	12.79	13.59
					(14.4)	(8.5)	(15.8)	(7.9)	(2.52)	(2.20)	(2.38)	(2.04)
1995	5030	1886	6486	2112	43.3	39.1	43.7	36.9	13.00	13.59	12.83	13.62
					(14.3)	(8.8)	(15.6)	(8.3)	(2.51)	(2.20)	(2.33)	(2.04)
1996	3755	1504	4928	1684	43.7	39.6	43.7	37.4	13.25	13.74	13.04	13.79
					(14.4)	(9.2)	(15.8)	(8.6)	(2.46)	(2.14)	(2.28)	(2.03)
1997	3949	1390	4968	1587	44.1	40.0	43.8	37.9	13.14	13.84	12.97	13.80
					(14.4)	(9.2)	(15.5)	(8.8)	(2.65)	(2.11)	(2.47)	(2.07)
1998	4101	1437	5185	1651	43.4	40.5	43.7	38.5	-	-	-	-
					(14.6)	(9.5)	(15.8)	(9.1)	(-)	(-)	(-)	(-)
1999	3968	1397	5039	1594	44.8	41.4	44.3	39.2	13.13	13.85	12.98	13.83
					(14.4)	(9.4)	(15.5)	(9.2)	(2.62)	(2.18)	(2.43)	(2.09)
2000	4216	1402	5500	1636	44.1	42.4	43.9	40.2	-	-	-	-
					(14.6)	(9.5)	(15.6)	(9.3)	(-)	(-)	(-)	(-)

[1]Standard deviations in parentheses

[2]Education data for 1998 and 2000 are unavailable.

Table 4.4: Summary Statistics of Demographic Variables - Part 2[1]

Year	Race (black)				Birth				Num.Children			
	Male		Female		Male		Female		Male		Female	
	Full	Sub	Full	Sub	Full	Sub	Full	Sub	Full	Sub	Full	Sub
1969	0.23	0.15	0.32	0.13	0.10	0.27	0.08	0.28	2.80	0.89	3.02	0.92
	(0.42)	(0.35)	(0.46)	(0.34)	(0.30)	(0.44)	(0.27)	(0.45)	(2.43)	(0.79)	(2.56)	(0.78)
1970	0.23	0.16	0.32	0.15	0.08	0.20	0.07	0.20	2.70	0.97	2.94	0.98
	(0.42)	(0.37)	(0.47)	(0.36)	(0.28)	(0.40)	(0.25)	(0.40)	(2.41)	(0.82)	(2.56)	(0.80)
1971	0.23	0.16	0.32	0.16	0.08	0.16	0.07	0.18	2.63	0.99	2.88	1.02
	(0.42)	(0.37)	(0.47)	(0.36)	(0.26)	(0.36)	(0.25)	(0.38)	(2.41)	(0.85)	(2.54)	(0.85)
1972	0.24	0.18	0.32	0.17	0.08	0.18	0.07	0.18	2.53	1.06	2.81	1.10
	(0.43)	(0.38)	(0.47)	(0.37)	(0.27)	(0.38)	(0.25)	(0.39)	(2.39)	(0.87)	(2.53)	(0.86)
1973	0.24	0.18	0.32	0.16	0.08	0.18	0.07	0.19	2.45	1.12	2.74	1.12
	(0.43)	(0.38)	(0.47)	(0.37)	(0.27)	(0.39)	(0.25)	(0.39)	(2.35)	(0.90)	(2.51)	(0.89)
1974	0.25	0.18	0.33	0.16	0.08	0.17	0.07	0.17	2.36	1.16	2.68	1.16
	(0.43)	(0.38)	(0.47)	(0.37)	(0.27)	(0.38)	(0.25)	(0.38)	(2.32)	(0.90)	(2.48)	(0.89)
1975	0.25	0.19	0.33	0.17	0.08	0.15	0.06	0.16	2.33	1.17	2.63	1.18
	(0.44)	(0.39)	(0.47)	(0.38)	(0.27)	(0.36)	(0.25)	(0.37)	(2.29)	(0.90)	(2.45)	(0.90)
1976	0.26	0.20	0.33	0.18	0.08	0.17	0.07	0.17	2.29	1.23	2.59	1.24
	(0.44)	(0.40)	(0.47)	(0.38)	(0.27)	(0.38)	(0.25)	(0.38)	(2.27)	(0.92)	(2.41)	(0.92)
1977	0.26	0.20	0.33	0.19	0.08	0.15	0.07	0.16	2.25	1.26	2.56	1.27
	(0.44)	(0.40)	(0.47)	(0.39)	(0.27)	(0.36)	(0.25)	(0.37)	(2.23)	(0.93)	(2.38)	(0.93)
1978	0.27	0.20	0.34	0.19	0.08	0.15	0.06	0.15	2.24	1.30	2.55	1.29
	(0.45)	(0.40)	(0.47)	(0.39)	(0.27)	(0.35)	(0.25)	(0.35)	(2.20)	(0.91)	(2.36)	(0.92)
1979	0.28	0.21	0.34	0.20	0.09	0.15	0.07	0.17	2.21	1.36	2.50	1.35
	(0.45)	(0.41)	(0.47)	(0.40)	(0.28)	(0.36)	(0.26)	(0.37)	(2.18)	(0.91)	(2.32)	(0.91)
1980	0.29	0.21	0.34	0.20	0.09	0.15	0.07	0.16	2.20	1.40	2.48	1.40
	(0.45)	(0.41)	(0.48)	(0.40)	(0.28)	(0.36)	(0.26)	(0.37)	(2.14)	(0.91)	(2.29)	(0.91)
1981	0.29	0.21	0.35	0.20	0.07	0.13	0.06	0.13	2.20	1.43	2.47	1.43
	(0.45)	(0.41)	(0.48)	(0.40)	(0.26)	(0.34)	(0.25)	(0.34)	(2.11)	(0.90)	(2.27)	(0.91)
1982	0.29	0.22	0.35	0.21	0.07	0.13	0.07	0.13	2.19	1.46	2.46	1.45
	(0.45)	(0.41)	(0.48)	(0.41)	(0.26)	(0.33)	(0.25)	(0.33)	(2.09)	(0.92)	(2.24)	(0.93)
1983	0.29	0.22	0.35	0.21	0.07	0.12	0.06	0.12	2.17	1.47	2.44	1.46
	(0.46)	(0.41)	(0.48)	(0.41)	(0.26)	(0.32)	(0.24)	(0.33)	(2.07)	(0.92)	(2.21)	(0.93)
1984	0.30	0.22	0.35	0.22	0.07	0.11	0.06	0.12	2.16	1.48	2.42	1.47
	(0.46)	(0.42)	(0.48)	(0.41)	(0.26)	(0.32)	(0.24)	(0.32)	(2.04)	(0.93)	(2.19)	(0.94)
1985	0.30	0.23	0.35	0.22	0.06	0.10	0.05	0.10	2.15	1.46	2.40	1.46
	(0.46)	(0.42)	(0.48)	(0.42)	(0.24)	(0.30)	(0.23)	(0.30)	(2.02)	(0.93)	(2.16)	(0.94)

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Table 4.4 – Continued

Year	Race (black)				Birth				Num.Children			
	Male		Female		Male		Female		Male		Female	
	Full	Sub	Full	Sub	Full	Sub	Full	Sub	Full	Sub	Full	Sub
1986	0.30	0.23	0.35	0.22	0.07	0.11	0.06	0.11	2.15	1.46	2.39	1.46
	(0.46)	(0.42)	(0.48)	(0.41)	(0.25)	(0.31)	(0.23)	(0.32)	(2.00)	(0.94)	(2.13)	(0.94)
1987	0.30	0.22	0.35	0.22	0.06	0.09	0.06	0.10	2.14	1.47	2.38	1.47
	(0.46)	(0.42)	(0.48)	(0.41)	(0.24)	(0.29)	(0.23)	(0.30)	(1.97)	(0.95)	(2.11)	(0.95)
1988	0.29	0.22	0.35	0.22	0.06	0.08	0.05	0.09	2.13	1.44	2.37	1.45
	(0.46)	(0.42)	(0.48)	(0.41)	(0.23)	(0.28)	(0.22)	(0.28)	(1.95)	(0.95)	(2.09)	(0.94)
1989	0.29	0.22	0.35	0.22	0.06	0.09	0.05	0.09	2.12	1.42	2.36	1.43
	(0.45)	(0.41)	(0.48)	(0.41)	(0.23)	(0.28)	(0.22)	(0.28)	(1.94)	(0.95)	(2.07)	(0.94)
1990	0.24	0.21	0.28	0.21	0.06	0.08	0.05	0.08	2.21	1.41	2.46	1.40
	(0.42)	(0.41)	(0.45)	(0.41)	(0.23)	(0.27)	(0.22)	(0.27)	(2.00)	(0.96)	(2.10)	(0.96)
1991	0.23	0.20	0.28	0.20	0.05	0.08	0.05	0.08	2.20	1.35	2.44	1.37
	(0.42)	(0.40)	(0.45)	(0.40)	(0.23)	(0.27)	(0.22)	(0.27)	(1.96)	(0.97)	(2.07)	(0.96)
1992	0.23	0.20	0.27	0.20	0.06	0.08	0.05	0.08	2.20	1.34	2.42	1.35
	(0.42)	(0.40)	(0.44)	(0.40)	(0.23)	(0.28)	(0.21)	(0.27)	(1.96)	(0.97)	(2.02)	(0.96)
1993	0.29	0.21	0.34	0.21	0.05	0.06	0.05	0.06	2.07	1.33	2.32	1.35
	(0.45)	(0.41)	(0.47)	(0.40)	(0.21)	(0.24)	(0.21)	(0.24)	(1.87)	(0.97)	(1.96)	(0.97)
1994	0.29	0.21	0.35	0.21	0.05	0.07	0.04	0.06	2.06	1.29	2.31	1.32
	(0.46)	(0.41)	(0.48)	(0.40)	(0.21)	(0.25)	(0.19)	(0.24)	(1.83)	(0.98)	(1.92)	(0.97)
1995	0.29	0.22	0.35	0.21	0.04	0.06	0.04	0.06	2.06	1.25	2.30	1.28
	(0.45)	(0.41)	(0.48)	(0.41)	(0.20)	(0.24)	(0.20)	(0.24)	(1.83)	(0.97)	(1.89)	(0.97)
1996	0.25	0.21	0.32	0.21	0.05	0.07	0.05	0.07	2.05	1.24	2.22	1.28
	(0.43)	(0.41)	(0.47)	(0.41)	(0.22)	(0.25)	(0.21)	(0.26)	(1.74)	(0.98)	(1.74)	(0.99)
1997	0.21	0.18	0.29	0.19	0.04	0.05	0.04	0.05	2.08	1.23	2.23	1.26
	(0.41)	(0.38)	(0.45)	(0.39)	(0.19)	(0.21)	(0.19)	(0.21)	(1.76)	(0.98)	(1.76)	(0.98)
1998	0.23	0.18	0.31	0.19	0.04	0.06	0.04	0.06	2.00	1.19	2.21	1.21
	(0.42)	(0.38)	(0.46)	(0.39)	(0.21)	(0.23)	(0.20)	(0.24)	(1.72)	(0.98)	(1.74)	(0.98)
1999	0.21	0.17	0.30	0.18	0.04	0.05	0.04	0.06	2.06	1.18	2.23	1.18
	(0.41)	(0.38)	(0.46)	(0.38)	(0.20)	(0.23)	(0.20)	(0.23)	(1.69)	(0.98)	(1.73)	(0.98)
2000	0.24	0.18	0.32	0.18	0.04	0.04	0.04	0.05	2.00	1.15	2.19	1.16
	(0.43)	(0.38)	(0.47)	(0.39)	(0.20)	(0.20)	(0.20)	(0.21)	(1.71)	(0.99)	(1.71)	(0.99)

[1]Standard deviations in parentheses

Table 4.5: Summary statistics of Labor Market Variables[1]

Year	Participation(%)				Hours worked[2]				Wage[3]			
	Male		Female		Male		Female		Male		Female	
	Full	Sub	Full	Sub	Full	Sub	Full	Sub	Full	Sub	Full	Sub
1969	97.5	100	61.1	68.3	2231	2315	1307	742	13.98	12.34	8.11	6.17
	(15.7)	(0.0)	(0.488)	(0.466)	(698)	(732)	(772)	(778)	(9.95)	(6.04)	(5.87)	(5.79)
1970	96.8	98.9	60.6	65.4	2180	2198	1325	821	13.99	13.17	8.24	6.26
	(17.6)	(10.5)	(48.9)	(47.7)	(722)	(698)	(756)	(822)	(9.68)	(7.78)	(5.61)	(6.28)
1971	96.0	97.8	60.4	64.4	2167	2190	1337	791	14.10	13.00	8.76	6.97
	(19.7)	(14.7)	(48.9)	(48.0)	(693)	(750)	(766)	(823)	(9.83)	(6.74)	(7.74)	(8.72)
1972	95.8	98.9	58.2	61.1	2190	2230	1369	799	14.50	14.05	8.90	6.28
	(20.1)	(10.4)	(49.3)	(48.8)	(714)	(709)	(757)	(852)	(9.63)	(8.33)	(6.44)	(6.95)
1973	95.0	98.8	59.1	66.3	2196	2226	1383	800	14.71	14.26	9.17	6.73
	(21.9)	(11.1)	(49.2)	(47.3)	(674)	(648)	(744)	(824)	(10.43)	(7.86)	(7.86)	(7.37)
1974	94.0	98.3	59.6	62.3	2117	2134	1361	791	14.71	14.51	9.05	6.38
	(23.8)	(12.8)	(49.1)	(48.5)	(702)	(708)	(730)	(829)	(13.66)	(16.69)	(7.84)	(8.67)
1975	92.4	97.8	60.7	64.5	2088	2093	1363	810	14.17	13.73	8.95	6.48
	(26.4)	(14.7)	(48.9)	(47.9)	(721)	(738)	(741)	(847)	(12.16)	(15.29)	(6.69)	(7.75)
1976	92.3	97.1	60.5	64.6	2108	2126	1392	829	14.50	13.89	9.30	6.71
	(26.7)	(16.7)	(48.9)	(47.8)	(722)	(726)	(711)	(828)	(10.53)	(8.19)	(7.57)	(7.27)
1977	92.1	98.0	61.0	0.672	2118	2185	1418	862	14.75	14.02	9.43	7.01
	(27.0)	(14.2)	(48.8)	(47.0)	(720)	(700)	(731)	(828)	(10.69)	(7.60)	(10.10)	(9.68)
1978	91.7	97.7	62.9	70.0	2132	2196	1441	973	15.52	14.45	9.14	6.86
	(27.6)	(14.8)	(48.3)	(45.8)	(713)	(692)	(722)	(861)	(26.78)	(7.84)	(6.89)	(6.94)
1979	91.5	97.8	64.4	73.0	2097	2155	1427	975	15.04	15.40	9.15	7.20
	(27.9)	(14.6)	(47.9)	(44.4)	(712)	(697)	(736)	(857)	(14.22)	(14.62)	(7.48)	(7.60)
1980	90.3	97.7	64.1	72.2	2069	2140	1438	949	13.93	13.84	8.82	6.82
	(29.6)	(15.1)	(48.0)	(44.8)	(715)	(723)	(722)	(834)	(8.92)	(7.60)	(9.03)	(7.75)
1981	89.2	97.5	63.1	71.2	2044	2111	1457	962	13.69	13.94	8.57	6.67
	(31.0)	(15.6)	(48.3)	(45.3)	(717)	(707)	(717)	(858)	(9.43)	(9.30)	(7.41)	(9.81)
1982	87.3	96.6	63.1	70.5	2013	2057	1461	975	14.03	13.95	8.53	6.31
	(33.3)	(18.2)	(48.3)	(45.6)	(737)	(773)	(730)	(880)	(18.44)	(13.76)	(6.84)	(6.25)
1983	86.4	96.6	63.4	73.5	2029	2072	1468	1022	13.67	13.80	9.40	7.01
	(34.3)	(18.2)	(48.2)	(44.2)	(729)	(737)	(731)	(852)	(10.64)	(9.64)	(19.00)	(7.95)
1984	86.1	96.3	66.0	78.3	2106	2145	1527	1141	14.22	14.07	8.78	7.52
	(34.6)	(18.8)	(47.4)	(41.2)	(729)	(761)	(730)	(871)	(13.13)	(11.49)	(11.44)	(15.82)
1985	86.4	96.1	65.6	76.8	2099	2127	1555	1169	14.54	14.41	9.01	7.56
	(34.3)	(19.5)	(47.5)	(42.2)	(720)	(737)	(741)	(912)	(17.77)	(12.02)	(7.71)	(8.83)

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Table 4.5 – Continued

Year	Participation(%)				Hours worked[2]				Wage[3]			
	Male		Female		Male		Female		Male		Female	
	Full	Sub	Full	Sub	Full	Sub	Full	Sub	Full	Sub	Full	Sub
1986	86.0	96.5	66.1	78.7	2114	2142	1571	1206	14.34	14.57	9.31	7.77
	(34.7)	(18.4)	(47.3)	(40.9)	(729)	(752)	(712)	(880)	(13.06)	(10.70)	(7.57)	(7.49)
1987	85.8	95.9	67.2	79.6	2135	2156	1583	1235	14.40	14.78	9.55	8.35
	(35.0)	(19.8)	(47.0)	(40.3)	(715)	(758)	(725)	(878)	(13.91)	(11.82)	(8.31)	(9.94)
1988	85.9	96.2	67.5	80.9	2160	2174	1618	1286	14.53	15.03	9.58	8.45
	(34.8)	(19.1)	(46.8)	(39.3)	(724)	(764)	(718)	(879)	(14.01)	(11.36)	(7.77)	(9.22)
1989	85.5	96.1	69.0	83.1	2159	2172	1603	1299	14.88	14.90	9.80	8.94
	(35.2)	(19.3)	(46.3)	(37.5)	(708)	(757)	(719)	(865)	(35.34)	(12.21)	(12.66)	(12.71)
1990	84.3	96.4	65.0	83.0	2130	2173	1613	1335	13.34	14.89	9.45	8.98
	(36.3)	(18.5)	(47.7)	(37.5)	(702)	(751)	(720)	(879)	(11.57)	(11.88)	(10.51)	(13.24)
1991	84.0	96.1	65.0	83.5	2102	2147	1629	1364	13.58	14.92	9.48	8.99
	(36.7)	(19.4)	(47.7)	(37.1)	(724)	(742)	(724)	(900)	(12.48)	(13.42)	(7.96)	(9.37)
1992	83.0	95.3	64.4	83.0	2058	2087	1596	1340	17.03	17.43	11.40	10.57
	(37.5)	(21.2)	(47.9)	(37.6)	(754)	(789)	(731)	(876)	(69.25)	(21.34)	(15.35)	(15.69)
1993	82.8	95.5	67.4	82.3	2105	2103	1647	1365	15.92	17.33	11.98	10.83
	(37.8)	(20.8)	(46.9)	(38.1)	(699)	(758)	(716)	(896)	(17.51)	(19.50)	(15.15)	(15.07)
1994	83.3	95.8	69.0	84.3	2138	2161	1654	1405	15.55	16.49	10.75	9.89
	(37.3)	(20.1)	(46.3)	(36.4)	(696)	(722)	(713)	(866)	(18.23)	(16.37)	(11.28)	(10.36)
1995	83.0	95.6	69.5	83.6	2160	2162	1691	1422	15.38	16.12	11.03	10.39
	(37.5)	(20.5)	(46.0)	(37.0)	(692)	(750)	(702)	(881)	(18.96)	(15.96)	(21.95)	(16.17)
1996	84.8	95.7	70.5	84.3	2181	2164	1679	1418	16.08	16.81	11.14	10.58
	(35.9)	(20.3)	(45.6)	(36.4)	(672)	(738)	(715)	(865)	(16.77)	(17.41)	(14.87)	(18.35)
1997	78.5	92.9	64.0	79.8	2184	2126	1727	1385	16.09	16.44	11.36	9.52
	(41.1)	(25.6)	(48.0)	(40.1)	(637)	(794)	(680)	(906)	(22.76)	(20.20)	(19.14)	(10.37)
1998	86.0	96.0	71.9	85.2	2220	2248	1725	1456	15.92	17.19	11.11	10.24
	(34.7)	(19.7)	(45.0)	(35.5)	(679)	(732)	(701)	(866)	(15.23)	(15.53)	(11.97)	(9.04)
1999	79.2	92.6	66.2	79.9	2195	2094	1736	1375	17.78	17.74	12.34	10.34
	(40.6)	(26.1)	(47.3)	(40.1)	(646)	(798)	(690)	(906)	(22.68)	(19.85)	(20.07)	(10.63)
2000	85.1	94.3	73.4	84.5	2186	2134	1728	1454	16.96	18.66	11.48	10.93
	(35.7)	(23.2)	(44.2)	(36.2)	(682)	(782)	(701)	(887)	(19.41)	(20.65)	(11.74)	(11.07)

[1]Standard deviations in parentheses
[2]Annual hours supplied to labor market
[3]Real wage in 1990 dollars

Table 4.6: Regression Results of Wage Equations

Variable	h_{t-1}	h_{t-2}	d_{t-1}	d_{t-2}	age_t^2	$age_t \cdot edu$
Female	1.2259*	0.5342*	-0.0781*	-0.0735*	-2.9122*	0.1269*
	(0.0146)	(0.0146)	(0.0038)	(0.0037)	(0.2538)	(0.0245)
Male	0.9105*	0.4655*	-0.0922*	-0.0789*	-4.5726*	0.1099*
	(0.0128)	(0.0126)	(0.0077)	(0.0072)	(0.2067)	(0.0166)

Standard errors in parentheses

*Significant at 5% level

Table 4.7: Regression Results of Children Production Functions

Variable	$const$	Q_f/κ	Q_f^2/κ^2	Q_m/κ	Q_m^2/κ^2	μ_f	μ_m	B	edu_f	edu_m
Ind. specific	-1.045*	-2.421*	2.113*	0.251	-0.847	0.196*	0.223*	-0.010*	0.006	0.026*
productivity	(0.285)	(1.005)	(0.843)	(0.601)	(0.697)	(0.059)	(0.052)	(0.005)	(0.012)	(0.010)
Education	8.003*	4.462*	-2.347	-0.910	-0.692	0.536*	0.468*	-0.025*	0.110*	0.160*
level	(0.575)	(2.028)	(1.698)	(1.211)	(1.380)	(0.123)	(0.113)	(0.011)	(0.025)	(0.021)

Standard errors in parentheses

* Significant at 5% level

Table 4.8: Mean of Conditional Choice Probabilities - households

Probabilities	household choices (k)				Probabilities	household choices (k)	
	k_1	k_3	k_5	k_6		k_7	k_8
$p_k(H_{nt})$	0.0739	0.0311	0.6748	0.0122	$p_k(H_{nt})$	0.1716	0.0067
$p_{k_5}(H_{kt}^{(1)})$	0.7652	0.2520	0.7805	0.4704	$p_{k_8}(H_{kt}^{(1)})$	0.0099	0.2154
$p_{k_5}(H_{kt}^{(2)})$	0.8053	0.5914	0.8405	0.6552	$p_{k_8}(H_{kt}^{(2)})$	0.4997	0.6270

Table 4.9: Mean of Conditional Choice Probabilities - divorcees

Probabilities	female choices (k)		Probabilities	male choices (k)	
	kk_1	kk_2		kk_1	kk_2
$p_k(H_{ft})$	0.0428	0.0038	$p_k(H_{mt})$	0.0335	0.0025
$p_{kk_1}(H^{(1)}_{kft})$	0.9325	0.5520	$p_{kk_2}(H^{(1)}_{kmt})$	0.0202	0.5841
$p_{kk_1}(H^{(2)}_{kft})$	0.9992	0.9714	$p_{kk_2}(H^{(2)}_{kmt})$	0.4863	0.8781

Table 4.10: Mean of Child Investment (Q) and Exposure Length (B) - households

Estimates	household choices (k)				Estimates	household choices (k)	
	k_1	k_3	k_5	k_6		k_7	k_8
$Q_k(H_{nt})$	0.5066	0.5414	0.6009	0.5968	$Q_k(H_{nt})$	0.6386	0.6084
$Q_{k_5}(H^{(1)}_{knt})$	0.5405	0.5622	0.6116	0.6171	$Q_{k_8}(H^{(1)}_{knt})$	0.6695	0.6541
$Q_{k_5}(H^{(2)}_{knt})$	0.5385	0.5635	0.6102	0.6063	$Q_{k_8}(H^{(2)}_{knt})$	0.6561	0.6960
$Q^2_k(H_{nt})$	0.2634	0.3002	0.3750	0.3706	$Q^2_k(H_{nt})$	0.4247	0.3833
$Q^2_{k_5}(H^{(1)}_{knt})$	0.3023	0.3276	0.3886	0.3950	$Q^2_{k_8}(H^{(1)}_{knt})$	0.4658	0.4347
$Q^2_{k_5}(H^{(2)}_{knt})$	0.3007	0.3296	0.3874	0.3810	$Q^2_{k_8}(H^{(2)}_{knt})$	0.4418	0.5066
$B_k(H_{nt})$	1.7091	1.4710	1.0759	2.2131	$B_k(H_{nt})$	1.1334	1.4811
$B_{k_5}(H^{(1)}_{knt})$	1.8796	1.8278	0.9802	1.5720	$B_{k_8}(H^{(1)}_{knt})$	0.4371	1.8365
$B_{k_5}(H^{(2)}_{knt})$	1.6657	1.2628	0.9114	1.3174	$B_{k_8}(H^{(2)}_{knt})$	0.8470	2.8474

Table 4.11: Mean of Child Investment (Q) - divorcees

Estimates	female choices (k)		Estimates	female choices (k)	
	kk_1	kk_2		kk_1	kk_2
$Q_k(H_{ft})$	0.6297	0.6633	$Q^2_k(H_{ft})$	0.4156	0.4611
$Q_{kk_1}(H^{(1)}_{kft})$	0.6375	0.6753	$Q^2_{kk_1}(H^{(1)}_{kft})$	0.4265	0.4816
$Q_{kk_1}(H^{(2)}_{kft})$	0.6461	0.6363	$Q^2_{kk_1}(H^{(2)}_{kft})$	0.4555	0.4239

Table 4.12: Utility Parameter Estimates

Utility from labor participation			Utility from leisure with birth effect		
Variables	Female		Variables	Female	Male
$const$	1.3450*		b_{nt}	9.9667**	-0.0035
	(0.2667)			(6.0805)	(1.8842)
age_{nt}	6.8926*		$age_{nt} \times b_{nt}$	-22.1200	9.9330
	(2.2007)			(34.6340)	(13.0433)
age^2_{nt}	-8.0326*		$age^2_{nt} \times b_{nt}$	20.6391	-17.1763
	(3.3394)			(51.9224)	(21.35842)
edu_n	0.0273*		$edu_n \times b_{nt}$	-0.4268*	0.0194
	(0.0108)			(0.1728)	(0.03202)
$race^{\ddagger}_n$	0.1401*		$race_n \times b_{nt}$	-1.1720**	-0.0513
	(0.0496)			(0.6143)	(0.1614)
Utility from leisure			**Utility from consumption**		
Variables	Female	Male	Variables	Female	Male
l_{nt}	1.3326**	12.3609*	c_{nt}	-0.0193	0.2237*
	(0.6880)	(0.5593)		(0.0321)	(0.0097)
$age_{nt} \times l_{nt}$	-4.3381**	3.5832**	c^2_{nt}	0.0033*	-0.0080*
	(2.2813)	(1.9826)		(0.0008)	(0.0007)
$age^2_{nt} \times l_{nt}$	6.6341*	1.2316			
	(3.1652)	(2.8648)			
$edu_n \times l_{nt}$	0.1247*	-0.1031*	**Utility from offspring**		
	(0.0313)	(0.0103)	Variables		
$race_n \times l_{nt}$	0.0285	0.6214*	$\ln \mu_{n''}$	0.6371*	
	(0.0568)	(0.0477)		(0.0797)	
l^2_{nt}	-2.3495*	-9.5750*	$edu_{n''}$	0.3058*	
	(0.6033)	(0.3229)		(0.0387)	
$l_{nt} \times l_{n't}$	0.2564*				
	(0.1228)				
Parameters	$\boldsymbol{\delta}_f$	$\boldsymbol{\delta}_m$	κ	δ_c	π
	0.7574*	1.0436*	0.2292*	1.2014*	0.9781*
	(0.1762)	(0.0396)	(0.0491)	(0.1219)	(0.0434)

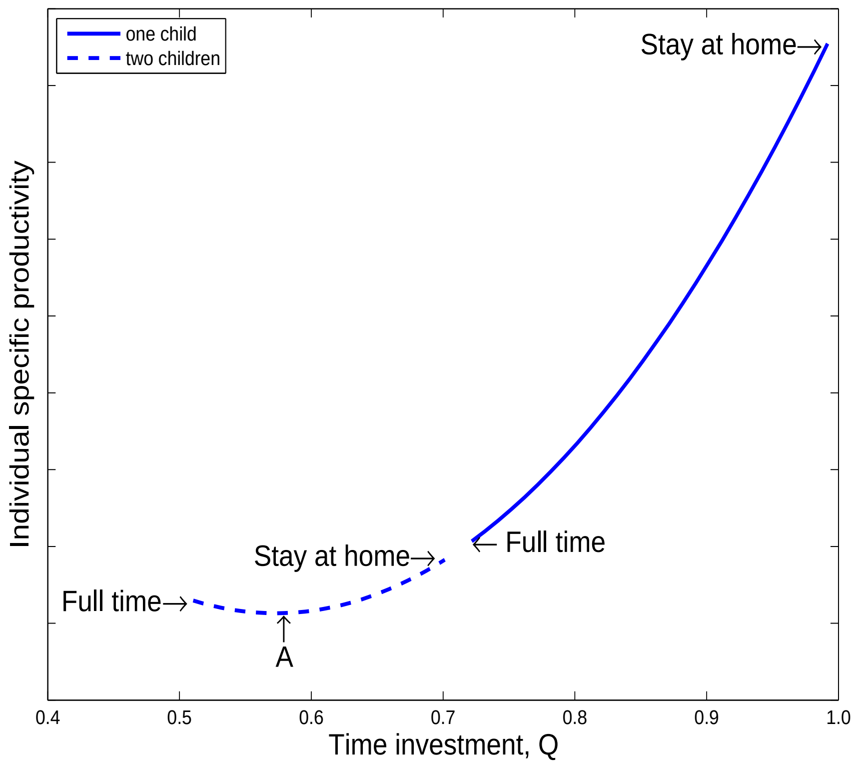
Standard errors in parentheses

‡ race = being black

* Significant at 5% level

** Significant at 10% level

Figure 4.1: Time Investment and Individual Specific Productivity of a Child



Chapter 5

Policy Evaluation

Governments have implemented or considered a number of policies to affect family structure and the labor supply within families. It is important to evaluate the consequences of each policy before actually implementing them. When completing such an analysis, it is crucial to account for the endogeneity of most of the choice variables. For example, a policy proposed to increase the fertility rate may affect the labor/leisure trade off in a family and could result in a less desirable level of fertility. A structural model in which this endogeneity is explicitly modeled can address this problem. In addition to this general advantage of structural estimation, the model presented in this paper can answer the question of what the effect of such policies on both the current and the future generation would be. Given the fact that effects of policy arise in a dynamic environment, it is important to measure the effects on both generations. For instance, achieving a desired level of fertility with a much less productive future generation is surely not the ultimate goal of policy. By assessing the consequences of policies in an intergenerational setting, we can more clearly understand the true benefits and potential costs of the programs.

This chapter presents the implications of some policies using the estimated household behavior model from the previous section. In particular the policies that are studied are a baby bonus, a marriage bonus and a parental training program. The marriage bonus turns out to be the most effective way to increase the fertility rate and enhance the future labor market outcome of children. The baby bonus increases fertility only very slightly. Parental training boosts the fertility rate and also increases the productivity of the second generation; however, the magnitude is less than that of the marriage bonus. I also perform an experiment where I change the relative wages of parents and children to determine the effect of such a change on parental choices. It is shown that wage changes over generations alters the behavior of people. When this is interpreted as a deficit financing, this is contrast to the theoretical argument for Ricardian Equivalence. The experiment decreases the fertility rate, and the outcome of children in the future is less desirable.

5.1 Simulation Scheme

I simulate the life of families for 25 years. To investigate the different implications of each policy across the characteristics of families, I divide the simulated sample into 10 subgroups according to the race and the education level of each spouse. The groups are summarized in Table 5.1. The division is based on the actual number of observations in the data used in this paper. For example, the number of couples in which one spouse is highly educated while the other is very poorly educated and the number of inter-race couples are limited; hence, they are excluded from the group specification.[1]

The state variables for each group are labor supply histories of each spouse, number of children, each child's age and time investment of the mother in each child. Due to the size of the state space, I consider a discrete working choice and restrict the maximum number of children to three. Also, the time investment in each child is discretized into 11 intervals. The age of each spouse when the family is formed is taken from the mode of the age at the first marriage in each group. The education level of each spouse is set at the mode of the group, and the individual specific productivity of each spouse is set at the mean of the group to which he or she belongs. I set the aggregate shock to be the mean of the time fixed effects during the study period. The implication of each policy should be understood bearing in mind these discrepancies between the data and the simulation. Each family has 12 choices in Table 4.1, and once a couple divorces the choice set is limited to labor participation decisions.

I examine the effect of different policies on fertility, female labor market participation and the divorce rate. The total fertility rate, which measures the average number of children that would be born to a woman over her fertile lifetime, is used to measure the fertility rate in the simulation.[2] An annual labor market participa-

[1] In practice, only groups with more than 25 incidents are studied.

[2] In the simulation I assume that a woman is fertile for all 25 years of the simulation. The mode

tion rate of married women is used to represent female labor supply. The divorce rate is the proportion of couples who end up divorcing. Furthermore, I evaluate the changes in the future outcome of children for each policy by incorporating the children production functions.

Since the model does not take into account the children generation's choice behavior in their adulthood, it is not possible to determine their labor supply, as is needed to predict their wages. Therefore, I assume that the children have full time labor supply for the past two years.[3] Also, since I cannot predict the gender of children, the mean of female children's and male children's future predicted wage is reported. The dynamic program is solved for 500 simulations for each group. For any policy implemented, the same draws for the private shock are used.

First I simulate the model without imposing any policy. This is done to see how closely the model predicts the behavior observed in the data and to have a baseline to compare the outcomes when the policies are applied. I label this non-policy simulation P-NO. The results of simulation P-NO are presented in Table 5.2 and Table 5.3. In general the model simulation predicts fertility and female labor market participation that are higher than what the actual data show, and the divorce rate tends to be under-predicted for black couples. The difference between data and P-NO simulation results may come from the fixed effects treatment, both individual specific productivity and time fixed effect, coarse discretization of time investment in children, the uniform age profile and education level, and the absence of continuous hours worked in the simulation exercise. All of these factors contribute to the heterogeneity in the population, and the different behavior pattern between data and simulation cannot be avoided.

5.2 Baby Bonus

The decline in fertility is becoming an important issue in many developed countries as they experience less than replacement fertility. Some countries have implemented a so-called baby bonus policy in which they pay cash to a household with a newborn. Whether such a policy is actually effective has been controversial. In this paper, I

of female age at the first marriage in groups ranges from 16 to 22, which makes the latest fertile age 47. This is consistent with the standard assumptions about when women can bear children.

[3] As long as all of children have the same amount of labor supply history, the effect of each policies on the future wage of children is unchanged.

implemented a baby bonus policy which is labeled P-BB. In this policy, a couple gets \$4500 in the year when a new child is born.[4] The results shown in Table 5.2 and Table 5.3 show that the effect of the policy on the fertility rate is minimal. Also the policy does not affect the labor supply behavior of married women. Divorce is a little less common under the policy, possibly due to the increased number of children. However, the size of changes for all choice behaviors are small enough not to have any effect on the future wage of children. This result implies that the policy is not effective enough to achieve the intended goal of increasing fertility.

5.3 Marriage Bonus

The results in this paper confirm prior evidence (and conventional wisdom) indicating that family disruption harms children.[5] A policy to reduce family disruption could then potentially increase welfare by improving the outcome of future generations. Policymakers have indeed expressed concern over various manifestations of the ills of family disruption, including concern about single motherhood and the direct harm of divorce on children. West Virginia and Washington, D.C. both implemented programs to directly subsidize low income couples who remain in a marriage, and the "marriage penalty" built into the US tax code receives significant attention whenever Congress considers major changes in the tax code. Most recently, British Conservatives have pressed for using the tax code to effectively provide a bonus to promote marriage.

I evaluate such a policy, based primarily on the scheme used in West Virginia. A couple on welfare gets \$100 per month when married. I use the poverty line corresponding the number of people in the household to limit people who can get this marriage bonus in my simulation. The results can be found in Table 5.2 and Table 5.3 with label P-MB. The policy induces a large decrease in the divorce rate. It might seem that \$100 per month is not enough money to make divorce less appealing. However, considering that the agents are forward looking, the discounted net present value of such an amount could have a big effect on behavior. Since one can get a steady flow of extra income when remaining married, divorce is much less attractive

[4]The amount of \$4500 is close to the high end of baby bonus policies in place. For example (using the October 2009 exchange rate), Singapore pays US\$2858 for the first and the second child and US\$4287 for the third and the fourth. Australia pays US\$4623 for each child.

[5]See Ribar Ribar [2004] for a survey of the papers studying the effect of family structure on children's well-being.

to couples.

Now, since divorce is an unappealing option, people consider having additional children as a good source of higher utility. This is due to the fact that divorce lowers the level of children production functions that are directly related to the level of utility each parent can get. That is, as people realize that divorce is less likely to happen in the future, they can expect more utility from having additional children. This pattern can be seen in the results, since the marriage bonus is the most effective policy for increasing fertility. Furthermore having more children itself enforces the incentive to stay married since parents anticipate the negative effect of divorce on the future of their children.

The labor supply of married females increases under the policy. This is likely primarily a result of the fact that dual income couples are more likely to divorce when there is no such policy. In other words, as the policy makes the divorce option less appealing, it draws more couples in which females work into the married couple pool. Finally, the decreased divorce rate has positive effect on the children's future wage.

In sum, the marriage bonus policy generates productive population growth. This is a desirable outcome, especially in light of concerns with the solution of current social security systems. The effects of the policy differs by group, however, highlighting the importance of tailoring the policy implementation based on characteristics of the target population.

5.4 Parental Training

One of the policies that is aimed at enhancing the outcome of children is a parental training program.[6] This policy provides the opportunity to learn how to parent effectively, to detect some merits or disadvantages of the child and to prevent abuse. I investigate such a policy, labeled P-PT. Under this policy, mothers are trained sufficiently through the parental training program such that they can apply the same

[6]Examples include Training of Parents in Schoolwork, Parents as Teachers Program, Megaskills program and Illinois Model Early Childhood Parental Training Program. A summary of some such programs is available at http://www.ncrel.org/sdrs/areas/issues/envrnmnt/famncomm/pa1lk21.htm. Attempts to evaluate their success include Beane [1990], ISBE report [1992] or Wagner, Spiker, and Linn [2002]. Evaluation of these programs generally focuses on educational achievement, but the framework in this paper allows me to investigate the likely effects of such programs on the eventual welfare of children.

effort and increase the benefit to their children, or they can provide the same level of maternal input by putting in less effort. This can be implemented in the simulation by increasing the measure Q in equation 4.8. This change makes the resulting time investment for each child to be more than what the mothers actually invest. In practice, a child gets an extra 10% of time investment from the mother. As people foresee that their children will be more productive in the future, the policy is expected to increase fertility. This conjecture is mirrored in the results shown in the Table 5.2 and Table 5.3. In fact, the policy increases fertility for all groups. The biggest increase is experienced by the groups in which the male education level is lower than that of the female. In contrast, those groups with a highly educated male partner show the least increase in fertility. The policy leads to a decrease in labor market participation of married women although the changes are not large. This implies that females acknowledge the fact that if they provide the same level of pre-policy labor supply, then each child would get less time investment since the number of children is bigger under the policy. Although this decreased amount of time investment could be offset by the parental training itself, the simulation results show the offset is not big enough to cover the cost of putting less time investment in each child.[7] Furthermore, by reducing the labor supply, females do enjoy more utility from leisure while expecting to have more productive children in the future.

For all groups, many couples who would have divorced stay married under the policy. Since utility from offspring is specified as the sum of that from each child, having more children gives parents a bigger incentive to stay married. That is, parents recognize the more severe consequences of being divorced when they have more children.

As the policy intends, the future outcome of children is higher when the parental training policy is implemented. In particular, less educated groups enjoy higher increase in the productivity of the second generation. This positive effect of the parental training policy on the future labor market outcome of children is not only due to the effectively increased time investment in each child but also due to the decreased divorce rate resulting from the change in parental behavior under the policy.

[7]This is true only if the children production functions increase in the time investment for each child. As discussed earlier the relation is not monotonic. However, when there is more than one child, which is a likely event under this policy, the education level of children is increasing in maternal time investment and the individual specific productivity of children is more likely to increase in maternal time investment when the labor supply of the mother is small.

From these results, the parental training policy increases fertility, decreases labor supply of married females, increases wages for the children generation and decreases the divorce rate. Although the direction of the effect is the same for all the groups, the magnitude of the results are different among groups, implying that careful consideration should be given to the disparate impact the policy may have depending on the social, educational, and economic condition of the target population.

5.5 Intergenerational Substitution

Under the intergenerational substitution experiment, I examine the consequences of the timing of wage changes. Specifically I improve parents' wages at the expense of children's. A deficit financing policy of government can be an example of such experiment. That is, the government finances some expenditures by borrowing during the working years of the parents generation. It then pays back these loans with a tax on the income of the children. As the model does not allow bequests, this policy cannot perfectly capture all of the potential responses to government deficit financing. However, even if bequests are allowed, the model does not predict Ricardian Equivalence since the tax is levied on uncertain future income rather than being a simple lump sum tax and the fertility decision is endogenous.[8] Therefore, the experiment here describes how behavior changes in response to changes in the intergenerational incidence of wages, and the associated change in the terms of the tradeoff between parents' own welfare and the welfare of their children.

In actual simulations this is implemented by increasing the wage by 5% for the parents and lowering the wage by 3% for the children generation.[9] I let the individual specific productivity of children be the channel through which the experiment affects the future labor market outcome of children. That is, the decrease in wage is treated as a decrease in the individual specific productivity of the child. The change in wages on the children's generation is of course endogenous and must be determined simultaneously with the calculation of the effects of the experiment on parental choices.

The intergenerational substitution experiment will influence decisions about fertil-

[8]See Barsky, Mankiw, and Zeldes [1986] for an analysis of why Ricardian Equivalence does not hold with a proportionate tax on uncertain future income. Lapan and Enders [1990] study debt management policy with endogenous fertility.

[9]In terms of deficit financing, it is equivalent to lowering the income tax by 5% for the parents and raising the income tax rate by 3% for the children generation.

ity, divorce and time investment in children. Fertility determines population growth, while family structure and labor supply along with fertility determine the productivity of the children's generation. To be able to interpret the results in terms of deficit financing, I set the interest rate on the bond to 2.81% for 25 years. This scheme makes the budget clear when the children generation pays the tax while the size of children generation is endogeneously determined as the deficit financing policy is implemented.[10] I label this policy P-IS referring to "Intergenerational Sustitution." The results in Table 5.2 and Table 5.3 confirm that anticipating the decreased wage on children affects the decision making of parents. In general, the experiment reduces the fertility rate appreciably. This is predictable given the fact that children's outcome is not as high as before.

Females tend to reduce labor supply in response to the change of wages in their generation and children's generation. Having fewer children increases the time that can be spent on private leisure and they may prefer to enjoy private leisure given the reduced number of children.

The experiment increases the divorce rate by a lot. The most educated groups show the largest increase in the divorce rate. This may be due to the fact that an increase in wage has the most effect on high income people and income is correlated with the level of education. That is, under the experiment divorce becomes more attractive and is especially more attractive to highly educated people. Also, having fewer children makes divorce relatively more attractive than the absence of such a wage change since the negative effect of divorce through children's future outcome is less severe in the situation where the number of children is smaller. This increase in the divorce rate contributes to the fertility decrease as well since the model does not permit divorced women to bear a newborn. This divorce rate change affects the future labor outcome of children in a negative way, with all groups experiencing a decrease in the future wage of children.

In sum, the change of relative wages in favor of parents brings negative population growth and makes the divorce option more attractive, and the future generation is predicted to be less productive than they would have been without such a change. When this experiment is interpreted as a deficit financing of government, this results raise the question of how to finance policies. That is, a fertility policy financed by deficit financing as studied here may result in a less desirable level of fertility or even

[10] This budget clearing assumes that all of children become full time workers in the future.

decreased fertility. For example, financing a parental training program with deficits may lead to this undesirable outcome. In fact, depending on the size of the cost of program, the worst case under this scheme is to have both less productive people and fewer people.

Table 5.1: Simulation Groups

Group	Race	Education Level	
	couple	female	male
B1	black	HSD* only	no HSD
B2	black	HSD only	HSD only
B3	black	HSD only	more than HSD
B4	black	more than HSD	HSD only
B5	black	more than HSD	more than HSD
NB1	non-black	no HSD	no HSD
NB2	non-black	no HSD	HSD only
NB3	non-black	HSD only	no HSD
NB4	non-black	HSD only	HSD only
NB5	non-black	HSD only	more than HSD
NB6	non-black	more than HSD	HSD only
NB7	non-black	more than HSD	more than HSD

* High School Diploma

Table 5.2: Policy Simulation Results - black couples

Group		B1	B2	B3	B4	B5
	Data	2.111	2.312	2.554	1.926	1.945
	P-NO	2.485	2.663	2.986	2.813	2.729
BR	P-BB	2.493(+0.3%)	2.671(+0.3%)†	2.986(+0.0%)	2.815(+0.1%)	2.733(+0.2%)
	P-MB	2.935(+18.1%)	2.964(+11.3%)	2.999(+0.4%)	2.983(+6.0%)	2.979(+9.1%)
	P-PT	2.698(+8.6%)	2.810(+5.5%)	2.992(+0.2%)	2.883(+2.5%)	2.829(+3.7%)
	P-IS	1.712(−31.1%)	2.032(−23.7%)	2.947(−1.3%)	2.425(−13.8%)	2.203(−19.3%)
	Data	83.70	82.90	78.90	88.47	87.26
	P-NO	90.64	91.06	91.17	92.34	93.32
WR	P-BB	90.64(+0.0%)	91.07(+0.0%)	91.17(+0.0%)	92.34(−0.0%)	93.32(−0.0%)
	P-MB	91.88(+1.4%)	92.17(+1.2%)	92.19(+1.1%)	93.28(+1.0%)	94.16(+0.9%)
	P-PT	90.00(−0.7%)	90.43(−0.7%)	90.53(−0.7%)	91.78(−0.6%)	92.87(−0.5%)
	P-IS	90.43(−0.2%)	90.95(−0.1%)	91.18(+0.0%)	92.34(−0.0%)	93.19(−0.1%)
	Data	44.44	27.87	28.57	35.11	35.62
	P-NO	33.50	26.55	11.31	18.57	18.73
DR	P-BB	33.35(−0.4%)	26.32(−0.8%)	11.34(+0.2%)	18.54(−0.2%)	18.61(−0.6%)
	P-MB	17.46(−47.9%)	14.61(−45.0%)	8.24(−27.2%)	10.84(−41.7%)	8.85(−52.7%)
	P-PT	23.26(−30.6%)	18.71(−29.5%)	8.49(−25.0%)	13.99(−24.7%)	13.68(−27.0%)
	P-IS	55.47(+65.6%)	45.60(+71.8%)	13.84(+22.3%)	30.97(+66.8%)	35.57(+90.0%)
	P-NO	17.09	18.21	20.57	19.44	21.57
WG	P-BB	17.08(−0.0%)	18.21(+0.0%)	20.57(−0.0%)	19.44(−0.0%)	21.57(−0.0%)
	P-MB	17.74(+3.8%)	18.83(+3.4%)	21.10(+2.5%)	19.96(+2.7%)	22.07(+2.3%)
	P-PT	17.66(+3.3%)	18.68(+2.6%)	20.87(+1.4%)	19.73(+1.5%)	21.82(+1.2%)
	P-IS	16.76(−1.9%)	17.84(−2.0%)	20.33(−1.2%)	19.21(−1.2%)	21.29(−1.3%)

† The percentage changes when each policy is implemented compared to P-NO (baseline)

- BR: birth rate (total fertility rate), WR: annual married female labor participation rate (%), DR: portion of divorced couples (%)
- WG: future expected wage of children (mean of female and male wage given full time labor supply history)
- P-BB: Baby Bonus policy, P-MB: Marriage Bonus policy, P-PT: Parental Training program, P-RE: Integenerational Substitution experiment
- Number of observations in data: B1 (27), B2 (122), B3 (56), B4 (94), B5 (146)

Table 5.3: Policy Simulation Results - non-black couples

Group		NB1	NB2	NB3	NB4	NB5	NB6	NB7
BR	Data	2.108	2.263	2.033	2.003	2.054	1.639	1.786
	P-NO	2.661	2.363	1.893	2.440	2.708	1.858	2.929
	P-BB	2.666(+0.2%)†	2.373(+0.4%)	1.909(+0.9%)	2.450(+0.4%)	2.710(+0.1%)	1.869(+0.6%)	2.930(+0.0%)
	P-MB	2.951(+10.9%)	2.906(+23.0%)	2.828(+49.3%)	2.929(+20.1%)	2.971(+9.7%)	2.841(+52.9%)	2.990(+2.1%)
	P-PT	2.814(+5.8%)	2.654(+12.3%)	2.307(+21.9%)	2.666(+9.3%)	2.840(+4.9%)	2.230(+20.1%)	2.949(+0.7%)
	P-IS	2.052(−22.9%)	1.540(−34.8%)	0.957(−49.5%)	1.616(−33.8%)	2.149(−20.6%)	0.915(−50.7%)	2.747(−6.2%)
WR	Data	70.16	56.62	65.90	71.81	71.03	80.77	78.58
	P-NO	83.96	84.70	87.02	87.18	87.70	89.14	92.75
	P-BB	83.95(−0.0%)	84.71(+0.0%)	87.04(+0.0%)	87.17(−0.0%)	87.69(−0.0%)	89.14(−0.0%)	92.75(−0.0%)
	P-MB	85.68(+2.1%)	86.20(+1.8%)	88.53(+1.7%)	88.62(+1.7%)	88.73(+1.2%)	90.38(+1.4%)	92.96(+0.2%)
	P-PT	83.05(−1.1%)	83.81(−1.1%)	86.25(−0.9%)	86.41(−0.9%)	86.89(−0.9%)	88.47(−0.8%)	92.23(−0.6%)
	P-IS	83.90(−0.1%)	84.54(−0.2%)	86.61(−0.5%)	86.91(−0.3%)	87.63(−0.1%)	88.62(−0.6%)	92.73(−0.0%)
DR	Data	24.32	22.81	30.00	28.31	24.38	27.70	20.16
	P-NO	24.53	32.75	44.78	27.75	18.48	44.69	5.84
	P-BB	24.40(−0.5%)	32.51(−0.7%)	44.34(−1.0%)	27.48(−1.0%)	18.40(−0.4%)	44.34(−0.8%)	5.83(−0.2%)
	P-MB	13.90(−43.3%)	14.90(−54.5%)	15.62(−65.1%)	10.99(−60.4%)	8.35(−54.8%)	12.91(−71.1%)	2.98(−49.0%)
	P-PT	16.29(−33.6%)	20.86(−36.3%)	30.09(−32.8%)	18.64(−32.8%)	12.09(−34.6%)	31.35(−29.8%)	4.44(−24.0%)
	P-IS	43.20(+76.1%)	57.33(+75.0%)	72.50(+61.9%)	52.86(+90.5%)	36.16(+95.7%)	72.97(+63.3%)	12.14(+107.9%)
WG	P-NO	17.32	17.78	17.98	19.35	21.43	20.01	25.60
	P-BB	17.32(−0.0%)	17.77(−0.0%)	17.98(−0.0%)	19.35(−0.0%)	21.43(+0.0%)	20.01(+0.0%)	25.61(+0.0%)
	P-MB	17.75(+2.5%)	18.23(+2.5%)	18.37(+2.2%)	19.80(+2.4%)	21.89(+2.2%)	20.51(+2.5%)	25.85(+1.0%)
	P-PT	17.75(+2.5%)	18.22(+2.5%)	18.33(+1.9%)	19.63(+1.5%)	21.71(+1.3%)	20.34(+1.7%)	25.64(+0.1%)
	P-IS	17.02(−1.7%)	17.44(−1.9%)	17.77(−1.2%)	19.13(−1.1%)	21.21(−1.0%)	19.87(−0.7%)	25.49(−0.4%)

† The percentage changes when each policy is implemented compared to P-NO (baseline)

- BR: birth rate (total fertility rate), WR: annual married female labor participation rate (%), DR: portion of divorced couples (%)
- WG: future expected wage of children (mean of female and male wage given full time labor supply history)
- P-BB: Baby Bonus policy, P-MB: Marriage Bonus policy, P-PT: Parental Training program, P-RE: Integenerational Substitution experiment
- Number of observations in data: NB1 (37), NB2 (57), NB3 (60), NB4 (378), NB5 (242), NB6 (213), NB7 (873)

Chapter 6

Conclusion

This paper explores how parental choices affect children and how these effects influence parents' behavior. Ultimately, this permits us to assess the effects of several policies on parents and on the future outcome of children. The empirical results show that parental labor market decisions, fertility decisions and family disruption decisions play a significant role in determining the labor market outcome of children. Specifically, maternal time investment in children and the joint family dissolution decision affect the two important determinants of children's future wage, namely individual specific productivity and the education level. Also it is revealed that parents do get more utility if they expect their children to perform better in the labor market in the future. By modeling parents' utility to be dependent on this relation and using the decision making behavior of couples and divorcees, the underlying structure of individual preferences is recovered.

Apart from the obvious direct interest in learning about the preferences in question, these estimates from the structural model give us the ability to perform diverse policy experiments. Specifically, a baby bonus, a marriage bonus and a parental training program are studied along with an experiment examining the intergenerational substitution of relative wages. These policies and the experiment can influence fertility, labor supply, family disruption and the future labor market outcome of children. The policy simulation results show that a marriage bonus is the most effective way to encourage people to have more children, reduce family disruption and increase the future labor market outcome of children. A parental training program also generates more productive population growth but the effect is not as strong as the marriage bonus. On the other hand, the baby bonus policy produces virtually no change in the behavior of parents. Finally, the change in relative wages over generations does affect the choices and outcomes of both parents and children. When this is understood as changes in taxation, the results of this experiment contrast with the Ricardian Equivalence result that holds in simple models of deficit financing. Specifically, increased reliance on deficit financing reduces fertility, makes divorce more appealing and makes the next generation less productive.

From these results, it can be stated that policies that directly subsidize for the birth of child are not ideal as they have negligible effect on fertility even when using the higher end of the cash amount among such policies. A more effective approach for raising fertility focuses on lowering the cost of producing quality children by improving the productivity of parental time investment in children. Implementing such a policy is not trivial as it is not obvious what programs will be effective in improving the productivity of parents. Research and investment in such "parental training" programs seems desirable. Also marriage bonus policies should get more attention as they turn out to be the most effective.

The analysis of the effects of intergenerational substitution implies that caution should be exercised when determining how to fund any of these policies, since the means of financing could counteract the benefits of the policy itself. Finally, given the accelerating trend toward larger deficits in the U.S., it should be noted that such an approach to funding government expenditures can result in reduced fertility and may push the nation into the category of developed countries with declining populations.

Appendix

Proof of Proposition 1 Let $v_{k_s}(H_t)$ be the continuation value when the members of household choose action $k_s \in \{k_1, \ldots, k_n\}$ at t and the optimal actions for the following periods given the state variables H[1]:

$$v_{k_s}(H_t) = E_{t+1} \sum_{r=t+1}^{T} \sum_{a=1}^{n} \beta^{r-t} k_{a,r} \left[u_{k_a}(H_r) + \varepsilon_{k_a r} \right]$$

where $u_{k_s t} = \boldsymbol{\delta}_{ft} u_{f k_s t} + \boldsymbol{\delta}_{mt} u_{m k_s t}$. The probability of choosing action, k_s, is expressed by

$$\begin{aligned} p_{k_s}(H_t) &= Pr\left\{ k_s = \underset{k_a}{\text{argmax}}\ u_{k_a}(H_t) + \varepsilon_{t,k_a} + v_{k_a}(H_t), \forall a \in \{1, \ldots, n\}, a \neq s \right\} \\ &= E(k_s^* = 1 | H_t). \end{aligned}$$

Consider the conditional choice probability of action k_1,

$$\begin{aligned} p_{k_1}(H_t) &= E(k_1^* = 1 | H_t) \\ &= \int_{\varepsilon_{k_1}=-\infty}^{\infty} \int_{\varepsilon_{k_2}=-\infty}^{\varepsilon_{k_1}+u_{k_1 t}+v_{k_1 t}-u_{k_2 t}-v_{k_2 t}} \int_{\varepsilon_{k_3}=-\infty}^{\varepsilon_{k_1}+u_{k_1 t}+v_{k_1 t}-u_{k_3 t}-v_{k_3 t}} \cdots \\ &= \cdots \int_{\varepsilon_{k_{n-1}}=-\infty}^{\varepsilon_{k_1}+u_{k_1 t}+v_{k_1 t}-u_{k_{n-1} t}-v_{k_{n-1} t}} \int_{\varepsilon_{k_n}=-\infty}^{\varepsilon_{k_1}+u_{k_1 t}+v_{k_1 t}-u_{k_n t}-v_{k_n t}} dG(\varepsilon_{k_1}, \ldots, \varepsilon_{k_n} | H_t) \\ &= \int_{-\infty}^{\infty} G_1(\varepsilon_{k_1}, \varepsilon_{k_1} + u_{k_1 t} - u_{k_2 t} + v_{k_1 t} - v_{k_2 t}, \varepsilon_{k_1} + u_{k_1 t} - u_{k_3 t} + v_{k_1 t} - v_{k_3 t}, \\ &= \ldots, \varepsilon_{k_1} + u_{k_1 t} - u_{k_{n-1} t} + v_{k_1 t} - v_{k_{n-1} t}, \varepsilon_{k_1} + u_{k_1 t} - u_{k_n t} + v_{k_1 t} - v_{k_n t} | H_t) d\varepsilon_{k_1} \end{aligned}$$

where $G(\vec{\varepsilon}|H_t)$ is a joint distribution function of the error term given states, H_t, and $G_{k_1}(\vec{\varepsilon}|H_t) \equiv \partial G(\vec{\varepsilon}|H_t)/\partial \varepsilon_{k_1}$. Define $Q_k(\vec{\omega}, H_t)$ as:

$$Q_{k_s}(\vec{\omega}, H_t) = \int G_k(\varepsilon_{k_s} + u_{k_s t} - u_{k_1 t} + \omega_{k_s t} - \omega_{k_1 t}, \ldots,$$

[1] In detail, the state variables are age, race, education level, individual specific productivity (individual fixed effect), time fixed effect, the history of labor market supply of each member, number of children, an indicator of having a child the previous year, time investment in children, years exposed to the family dissolution and the ages of children.

$$\varepsilon_{k_s} + u_{k_st} - u_{k_{s-1}t} + \omega_{k_st} - \omega_{k_{s-1}t}, \varepsilon_{k_s}, \varepsilon_{k_s} + u_{k_st} - u_{k_{s+1}t} + \omega_{k_st} - \omega_{k_{s+1}t},$$
$$\ldots, \varepsilon_{k_s} + u_{k_st} - u_{tk_n} + \omega_{k_st}|H_t)d\varepsilon_{k_s}.$$

By defining $\vec{Q}(\vec{\omega}, H_t) = \{Q_{k_s}(\vec{\omega}, H_t)\}_{s=1}^{n}$ and letting $\vec{\omega} = \{v_{k_r} - v_{k_n}\}_{r=1}^{n-1}$, it can be stated that $p_{k_s}(H_t) = Q_{k_s}(\vec{\omega}, H_t)$ and consequently, $\vec{p}(H_t) = \vec{Q}(\vec{\omega}, H_t)$. Following proposition 1 in Hotz and Miller Hotz and Miller [1993], the vector of the differences of valuation functions can be expressed by a function of the vector of the conditional choice probabilities. Now let's consider the expected payoff in period t,

$$E(\sum_{s=1}^{n} k_s[u_{k_s}(H_t) + \varepsilon_{k_st}]|H_t) = \sum_{s=1}^{n} p_{k_s}(H_t)[u_{k_s}(H_t) + E(\varepsilon_{k_s}|H_t, k_s = 1)].$$

By using the fact that $Q_{k_s}^{-1}(\vec{p}(H_t)) = v_{k_s}(H_t) - v_{k_n}(H_t)$, the following equations show that the expected error term is a function of conditional choice probabilities:

$$\begin{aligned} & E(\varepsilon_{k_st}|H_t, k_s = 1) \\ = & \int \varepsilon G_{k_s}(\varepsilon + u_{k_st} - u_{k_1t} + Q_{k_st}^{-1} - Q_{k_1t}^{-1}, \ldots, \varepsilon + u_{k_st} - u_{k_{s-1}t} + Q_{k_st}^{-1} - Q_{k_{s-1}t}^{-1}, \varepsilon, \\ & \varepsilon + u_{k_st} - u_{k_{s+1}t} + Q_{k_st}^{-1} - Q_{k_{s+1}t}^{-1}, \ldots, \varepsilon + u_{k_st} - u_{k_nt} + Q_{k_st}^{-1}|H_t)/p_{k_s}(H_t)d\varepsilon. \end{aligned}$$

Denote the previous entity as $\varphi_{k_s}(\vec{p}(H_t))$. Suppose that the error term has a Type 1 extreme value distribution. Then it can be shown that

$$\begin{aligned} & Q_{k_s}^{-1}(\vec{p}(H_t)) - Q_{k_{s'}}^{-1}(\vec{p}(H_t)) = \ln p_{k_s}(H_t)/\ln p_{k_{s'}}(H_t) \\ & \varphi_{k_s}(\vec{p}(H_t)) - \varphi_{k_{s'}}(\vec{p}(H_t)) = \ln p_{k_{s'}}(H_t)/\ln p_{k_s}(H_t). \end{aligned} \quad (6.1)$$

Now the conditional valuation function is define as:

$$\begin{aligned} V_{kt} + \varepsilon_{kt} &= \max E_t[\sum_{r=t}^{T}\sum_{a=1}^{n} \beta^{r-t} k_{ar}(u_{k_ar} + \varepsilon_{k_ar})|k_{st} = 1] \\ &= u_{k_st} + \varepsilon_{k_st} + \max E_t \sum_{r=t+1}^{T}\sum_{a=1}^{n} \beta^{r-t} k_{ar}(u_{k_ar} + \varphi_{k_ar}). \end{aligned}$$

By the Bellman principle, this can restated as:

$$V_{k_st} = u_{k_st} + \beta E \sum_{a=1}^{n} p_{k_a,t+1}(V_{k_a,t+1} + \varphi_{k_a,t+1}).$$

Define $H_{k_st}^{(q)}$ to be the set of state variables at $t+q$ when the members of the household choose action k_s at t and the action path set by a researcher to achieve finite state dependence. Let denote $\{k^1, k^2, \ldots, k^q\}$ to be the sequence of actions along the path. If the path is followed from t, it can be stated that:

$$V_{k_st} = u_{k_st} + \beta E \sum_{a=1}^{n} p_{k_a}(H_{k_st}^{(1)})(V_{k_a}(H_{k_st}^{(1)}) + \varphi_{k_a}(H_{k_st}^{(1)})).$$

By adding and subtracting the following:

$$\beta E \sum_{a=1, a\neq k^1}^{n} [p_{k^1}(H_{k_st}^{(1)}) - p_{k_a}(H_{k_st}^{(1)})][V_{k^1}(H_{k_st}^{(1)}) + \varphi_{k^1}(H_{k_st}^{(1)})]$$

the previous equation becomes:

$$\begin{aligned} V_{k_st} \quad &= \quad u_{k_st} + \beta E\,[\,V_{k^1}(H_{k_st}^{(1)}) + \varphi_{k^1}(H_{k_st}^{(1)}) \\ &+ \quad \sum_{a=1, a\neq k^1}^{n} p_{k_a}(H_{k_st}^{(1)})\{V_{k_a}(H_{k_st}^{(1)}) - V_{k^1}(H_{k_st}^{(1)}) + \varphi_{k_a}(H_{k_st}^{(1)}) - \varphi_{k^1}(H_{k_st}^{(1)})\}\,]\,. \end{aligned} \tag{6.2}$$

By defining $A_{k_a|k^1}(H_{k_st}^{(1)}) \equiv V_{k_a}(H_{k_st}^{(1)}) - V_{k^1}(H_{k_st}^{(1)}) + \varphi_{k_a}(H_{k_st}^{(1)}) - \varphi_{k^1}(H_{k_st}^{(1)})$ and applying the same logic to one period further,

$$V_{k^1}(H_{k_st}^{(1)}) = u_{k^1}(H_{k_st}^{(1)}) + \beta E[V_{k^2}(H_{k_st}^{(2)}) + \varphi_{k^2}(H_{k_st}^{(2)}) + \sum_{a=1, a\neq k^2}^{n} p_{k_a}(H_{k_st}^{(2)}) A_{k_a|k^2}(H_{k_st}^{(2)})].$$

This expression is inserted in to equation 6.2, which yields

$$\begin{aligned} V_{k_st} \quad &= \quad u_{k_st} + \beta E[u_{k^1}(H_{k_st}^{(1)}) + \beta E(V_{k^2}(H_{k_st}^{(2)}) + \varphi_{k^2}(H_{k_st}^{(2)}) \\ &+ \quad \sum_{a=1, a\neq k^2}^{n} p_{k_a}(H_{k_st}^{(2)}) A_{k_a|k^2}(H_{k_st}^{(2)})) + \varphi_{k^1}(H_{k_st}^{(1)}) + \sum_{a=1, a\neq k^1}^{n} p_{k_a}(H_{k_st}^{(1)}) A_{k_a|k^1}(H_{k_st}^{(1)})]. \end{aligned}$$

A similar procedure can be applied to $V_{k^2}(H_{k_st}^{(2)}), V_{k^3}(H_{k_st}^{(3)}), \ldots, V_{k^q}(H_{k_st}^{(q)})$. Then the conditional valuation function is

$$\begin{aligned} V_{k_s t} &= u_{k_s t} + E\sum_{z=1}^{q}\beta^z[u_{k^z}(H^{(z)}_{k_s t}) + \varphi_{k^z}(H^{(z)}_{k_s t}) + \sum_{a=1,a\neq k^z}^{n} p_{k_z}(H^{(z)}_{k_s t})A_{k_a|k^z}(H^{(z)}_{k_s t}))] \\ &+ E\beta^{q+1}[V_{k^{q+1}}(H^{(q+1)}_{k_s t}) + \varphi_{k^{q+1}}(H^{(q+1)}_{k_s t}) + \sum_{a=1,a\neq k^{q+1}}^{n} p_{k_a}A_{k_a|k^{q+1}}(H^{(q+1)}_{k_s t})] \end{aligned}$$

where k^{q+1} is any action taken after following the assigned path from $t+1$ to $t+q$. Alternatively

$$\begin{aligned} V_{k_s t} &= u_{k_s t} + E\sum_{z=1}^{q}\beta^z[u_{k^z}(H^{(z)}_{k_s t}) + \varphi_{k^z}(H^{(z)}_{k_s t}) + \sum_{a=1,a\neq k^z}^{n} p_{k_z}(H^{(z)}_{k_s t})A_{k_a|k^z}(H^{(z)}_{k_s t}))] \\ &+ E\beta^{q+1}[\sum_{a=1}^{n} p_{k_a}(V_{k_a}(H^{(q+1)}_{k_s t}) + \varphi_{k_a}(H^{(q+1)}_{k_s t}))]. \end{aligned}$$

Recall that the specific distributional assumption of the error term gives the nice representation of the differences between conditional valuation functions and the expected value of the error term as in equation 6.1 from which $A_{k_a|k^b}(H^{(c)}_{k_s t}) = 0, \forall a, b \in \{1, \ldots, n\}, c \in \mathbb{N}$. Then the previous equation becomes

$$\begin{aligned} V_{k_s t} &= u_{k_s t} + E\sum_{z=1}^{q}\beta^z[u_{k^z}(H^{(z)}_{k_s t}) + \varphi_{k^z}(H^{(z)}_{k_s t})] \\ &+ E\beta^{q+1}[\sum_{a=1}^{n} p_{k_a}(V_{k_a}(H^{(q+1)}_{k_s t}) + \varphi_{k_a}(H^{(q+1)}_{k_s t}))]. \end{aligned} \tag{6.3}$$

Consider the pair of actions that exhibit finite state dependence, k_s and $k_{s'}$, of which associated sequence of paths are $\{k^1, k^2, \ldots, k^q\}$ and $\{k^{1'}, k^{2'}, \ldots, k^{q'}\}$. The difference between the conditional valuation functions associated with each action is

$$\begin{aligned} V_{k_s t} - V_{k_{s'} t} &= u_{k_s t} - u_{k_{s'} t} + E\sum_{z=1}^{q}\beta^z[u_{k^z}(H^{(z)}_{k_s t}) + \varphi_{k^z}(H^{(z)}_{k_s t}) - u_{k^{z'}}(H^{(z)}_{k_s t}) - \varphi_{k^{z'}}(H^{(z)}_{k_s t})] \\ &+ E\beta^{q+1}[\sum_{a=1}^{n} p_{k_a}\{V_{k_a}(H^{(q+1)}_{k_s t}) + \varphi_{k_a}(H^{(q+1)}_{k_s t})\} \\ &- \sum_{a=1}^{n} p_{k_a}\{V_{k_a}(H^{(q+1)}_{k_{s'} t}) + \varphi_{k_a}(H^{(q+1)}_{k_{s'} t})\}]. \end{aligned}$$

According to finite state dependence, $H_{k_s t}^{(q+1)} \equiv H_{k_{s'} t}^{(q+1)}$; hence, the last line of the previous expression cancels out. By exploiting the distributional assumption on the error terms the left hand side of the previous equation becomes the ratio of the log of relevant conditional choice probabilities. Finally,

$$\ln \frac{p_{k_s}(H_t)}{p_{k_{s'}}(H_t)} = u_{k_s t} - u_{k_{s'} t} + E \sum_{z=1}^{q} \beta^z \left[u_{k^z}(H_{k_s t}^{(z)}) - u_{k^{z'}}(H_{k_s t}^{(z)}) + \ln \frac{p_{k^{z'}}(H_{k_{s'} t}^{(z)})}{p_{k^z}(H_{k_s t}^{(z)})} \right] \tag{6.4}$$

which forms the base of the first set of moment conditions. The second set of moment conditions comes from the Euler equation. Given that the household optimally chooses the labor participation decisions of members, each member chooses the optimal hours to work, namely, $\partial V_{k_s t}/\partial h_{it} = 0$ for $i \in \{f, m\}$ and $k_s \in \{k_1, k_3, k_5, k_6, k_7\}$. Also once an individual goes through a divorce, the Euler equation applies when one decides to work, $\partial V_{kk_1 t}/\partial h_{it} = 0$ for $i \in \{f, m\}$. Again the recursive expression of equation 6.3 is used to get the Euler equation. Since h_{it} is not an element of $H_{k_s t}^{(q+1)}$,

$$\frac{\partial V_{k_s t}}{\partial h_{it}} = \frac{\partial u_{k_s t}}{\partial h_{it}} + E_t \sum_{z=1}^{q} \beta^z \frac{\partial \{u_{k^z}(H_{k_s t}^{(z)}) + \varphi_{k^z}(H_{k_s t}^{(z)})\}}{\partial h_{it}}.$$

By the distributional assumption of the error term, $\varphi_{k^z}(H_{t,k_s}^{(z)}) = \vartheta - \ln p_{k^z}(H_{t,k_s}^{(z)})$ with the Euler's constant ϑ. Then the Euler equation finally becomes the second set of moment conditions

$$\frac{\partial V_{k_s t}}{\partial h_{it}} = \frac{\partial u_{k_s t}}{\partial h_{it}} + E_t \sum_{z=1}^{q} \beta^z \left(\frac{\partial u_{k^z}(H_{k_s t}^{(z)})}{\partial h_{it}} - \frac{\partial p_{k^z}(H_{k_s t}^{(z)})}{p_{k^z}(H_{t,k_s}^{(z)}) \partial h_{it}} \right). \tag{6.5}$$

For each pair introduced in Table 4.2, equation 6.4 is applied, yielding five moment conditions. The Euler equation in equation 6.5 is applied to action k_1, k_5 and k_6 for married females who participate the labor market, action k_1, k_3, k_5 and k_7 for working married males, and action kk_1 for working female/male divorcees, which gives nine moment conditions. As a result, I have 14 moment conditions in total.

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