Three Essays on the Economics of Household Decision Making

DISSERTATION

Presented in Partial Fulfillment of the Requirements for
the Degree Doctor of Philosophy in the
Graduate School of The Ohio State University

By

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2010

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Abstract

My research emphasizes the role of interrelated preferences in determining economic choices within a household. In this regard, I study both intergenerational interactions (between parents and children) and intragenerational interactions (between spouses). These linkages have important implications on individual economic behavior such as savings, labor supply, investment in human capital, and bequests which in turn affects aggregate savings and growth. Standard altruism models developed by Barro and Becker are based on an important assumption that parents and children have homogeneous discount factors, which precludes any role parents can play in influencing their child’s time preferences. However, there is empirical evidence that parents attempt to shape their children’s attitudes. The first essay of my dissertation, “Tough Love and Intergenerational Altruism” (based on this I also have a joint work with Masao Ogaki), proposes a framework to study the role of parents in shaping children’s time preferences. The tough love altruism model modifies the standard altruism model in two ways. First, the child’s discount factor is endogenously determined so that low consumption at young ages leads to a higher discount factor later in her life. Second, the parent evaluates the child’s lifetime utility with a constant high discount factor. In contrast to the predictions of the standard model that transfers are independent of exogenous changes in the child’s discount factor, the tough love altruism model predicts that transfers from the parent will fall when the child’s discount factor falls. Thus, our model is more consistent with empirical evidence on parental punishments than the standard altruism model. The second essay, “Adolescent Substance Use and Intergenerational Transfers: Evidence from Micro Data,” provides empirical
evidence for the use of pecuniary incentives by the parent to influence child behavior. Using the first seven waves of the National Longitudinal Survey of Youth, 1997 (NLSY97), I measure the effect of child alcohol consumption on parental transfers. Owing to the plausible endogeneity of the child’s alcohol use in the regression equation of transfers she receives from parents, I estimate this relationship using an instrumental variable which utilizes variation in the price of alcoholic beverages over time and across states as a source of exogenous variation. The main finding of the paper is that after accounting for the possible endogeneity of substance use, the incidence of alcohol consumption among youths significantly reduces the amount of parental transfers they receive. Given the robust evidence for a negative correlation between youth substance use and their discount factor in the economics and psychology literature, this result provides an empirical basis for the tough love model of intergenerational altruism. The existing literature on joint retirement suggests that married couples tend to coordinate their retirement decisions which seem to be largely explained by the complementarity in their preferences for leisure. However, the recent trend toward increased labor force participation of older married women may make synchronization of retirement decisions more difficult as more recent cohorts of women become more strongly attached to the labor force and build their own careers, a fact that has been overlooked in the literature. My third essay, “Cross-Cohort Differences in Joint Retirement: Evidence from the Health and Retirement Study,” uses the Health and Retirement Study (HRS) data from 1992 through 2006 to document that the likelihood of a married couple jointly exiting the labor force (given that both were employed in the previous period) decreases across successive birth cohorts of wives. I then estimate a discrete choice multinomial model of labor force transition for married couples and find that, while economic factors have substantial power in explaining variation across married couples in retirement behavior, trends across cohorts in these factors do not contribute significantly towards explaining the observed cohort trend in joint retirement. This result suggests that non-economic factors, such
as changes in social norms and attitudes towards work, are likely to be more important explanations for this observed trend. From a policy perspective, an implication of this finding is that the bias in the estimated effect of a policy aimed at influencing older workers’ labor force behavior (caused by ignoring potential interactions in retirement decisions of spouses) can be mitigated if recent cohorts are less likely to retire together.
ACKNOWLEDGMENTS

I would like to thank Masao Ogaki for his advice, encouragement, and support towards the completion of this dissertation. His work ethics and discipline are a constant source of inspiration for me and he has contributed greatly in improving my understanding of how to conduct independent research. Pok-sang Lam has mentored me from the beginning of my research and also supported me financially for two quarters as his research assistant, and I am thankful to him for the role he has played in shaping my research.

I am grateful for the feedback and participation of my committee members. David Blau is instrumental in shaping my research interests in the area of labor economics. His encouragement and guidance has helped me cross the disciplinary boundary between Macroeconomics and Labor Economics. I have benefited greatly from my discussions with Paul Evans whose knowledge of the subject of Economics as a whole is awe-inspiring. I have gained significantly from his lucid explanations on a wide range of topics both inside and outside the class room.

I am grateful to Bruce Weinberg and Audrey Light for their insightful comments and suggestions on my research throughout my stay at the Ohio State University. I also want to thank my friend, Kent Zhao, for numerous discussions on computational economics methods and research in general.
Last, but most important, I thank my family for their love and support. I am exceptionally grateful to my parents for all the hard work they had to endure to provide me a good education. My wife, Mithuna was a constant source of encouragement and support. Her contribution towards the completion of my dissertation is immense and I am grateful for her suggestions, ideas and time.
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PUBLICATIONS


FIELD OF STUDY

• Major Field: Economics

• Areas of Specialization: Macroeconomics, Labor Economics, Applied Econometrics, Household Behavior and Family Economics
# Contents

Abstract ................................................................. ii

Acknowledgments ....................................................... v

Vita ........................................................................ vii

List of Tables ............................................................... x

List of Figures .............................................................. xii

Chapters:

1. Adolescent Substance Use and Intergenerational Transfers: Evidence from Micro Data 1
   1.1 Introduction ......................................................... 1
   1.2 Related Literature ............................................... 4
   1.3 Data ................................................................. 6
   1.4 How Youth Substance Use Affects Parental Transfers? .......... 8
   1.5 Why do parents react to children’s substance use by reducing transfers? .... 18
   1.6 Conclusion .......................................................... 21

2. Tough Love and Intergenerational Altruism ................................. 22
   2.1 Introduction ......................................................... 22
   2.2 A Review of Empirical Evidence ................................ 27
   2.3 A Consumption Good Economy ................................. 31
   2.4 How Important is Tough Love? ................................. 40
   2.5 Are Parents Loving in the Tough Love Altruism Model? ........ 45
   2.6 Tough Love Altruism Model with Leisure ...................... 49
   2.7 Conclusion .......................................................... 53
3. Cross-Cohort Differences in Joint Retirement: Evidence from the Health and Retirement Study ................................................................. 57
   3.1 Introduction ................................................................. 57
   3.2 Joint Retirement: Extent, Explanations and Relevance ......................... 58
   3.3 Are Recent Cohorts Less Likely to Retire Together? .......................... 59
   3.4 Data and Method ......................................................... 62
   3.5 Estimation Results ....................................................... 72
   3.6 Conclusion ............................................................... 77

Bibliography ................................................................. 88

Appendices:

A. Appendix for Chapter 2 ............................................... 96
   A.1 Redistributive Neutrality in Tough Love Altruism Model .................... 96
   A.2 Redistributive Neutrality in Endogenous Altruism Model .................... 98
   A.3 Simulation Results for Tough Love Altruism Model with alternative assumption about parameters ........................................... 102

B. Appendix for Chapter 3 ................................................. 105
   B.1 Robustness checks for alternative sets of sample restrictions ............. 105
# List of Tables

<table>
<thead>
<tr>
<th>Table</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1</td>
<td>Sample means in the NLSY97 (1997-2003)</td>
</tr>
<tr>
<td>1.2</td>
<td>Probit MLE Results</td>
</tr>
<tr>
<td>1.3</td>
<td>First Stage Estimates</td>
</tr>
<tr>
<td>1.4</td>
<td>Second Stage Estimates</td>
</tr>
<tr>
<td>2.1</td>
<td>Tough Love Altruism Model ($\sigma &gt; 1$)</td>
</tr>
<tr>
<td>2.2</td>
<td>Tough Love Altruism Model ($\sigma &lt; 1$)</td>
</tr>
<tr>
<td>2.3</td>
<td>Endogenous Altruism Model ($\sigma &gt; 1$)</td>
</tr>
<tr>
<td>2.4</td>
<td>Endogenous Altruism Model ($\sigma &lt; 1$)</td>
</tr>
<tr>
<td>2.5</td>
<td>Child’s lifetime Utility Comparison</td>
</tr>
<tr>
<td>2.6</td>
<td>Tough Love Altruism Model with Leisure</td>
</tr>
<tr>
<td>3.2</td>
<td>Labor Force Transition from Joint Employment in the base year, by Wife’s Birth Cohort</td>
</tr>
<tr>
<td>3.3</td>
<td>Selected Marginal Effects from Multinomial Logit Model of Joint Retirement</td>
</tr>
<tr>
<td>A.1</td>
<td>Tough Love Altruism Model ($\sigma &gt; 1$)</td>
</tr>
<tr>
<td>A.2</td>
<td>Tough Love Altruism Model ($\sigma &gt; 1$)</td>
</tr>
</tbody>
</table>
## List of Figures

<table>
<thead>
<tr>
<th>Figure</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.1 Age-Participation Profile for Selected Cohort of Married Women (Source: Author’s Calculation from IPUMS-CPS Data)</td>
<td>79</td>
</tr>
<tr>
<td>3.2 Cohort Trend in Joint Retirement</td>
<td>80</td>
</tr>
<tr>
<td>3.3 Probability of Both Exiting the Labor Force by Wife’s Birth Cohort</td>
<td>81</td>
</tr>
<tr>
<td>3.4 Probability of Only Husband Exiting the Labor Force by Wife’s Birth Cohort</td>
<td>82</td>
</tr>
<tr>
<td>3.5 Probability of Only Wife Exiting the Labor Force by Wife’s Birth Cohort</td>
<td>83</td>
</tr>
<tr>
<td>3.6 Probability of No One Exiting the Labor Force by Wife’s Birth Cohort</td>
<td>84</td>
</tr>
<tr>
<td>3.7 Probability of Both Exiting the Labor Force by Wife’s Birth Cohort, Conditional on at least One Spouse Retiring</td>
<td>85</td>
</tr>
<tr>
<td>3.8 Probability of Only Husband Exiting the Labor Force by Wife’s Birth Cohort, Conditional on at least One Spouse Retiring</td>
<td>86</td>
</tr>
<tr>
<td>3.9 Probability of Only Wife Exiting the Labor Force by Wife’s Birth Cohort, Conditional on at least One Spouse Retiring</td>
<td>87</td>
</tr>
<tr>
<td>B.1 Predicted Transition Probabilities by Wife’s Birth Cohort</td>
<td>106</td>
</tr>
<tr>
<td>B.2 Predicted Transition Probabilities by Wife’s Birth Cohorts, Conditional on at least One Spouse Retiring</td>
<td>107</td>
</tr>
<tr>
<td>B.3 Predicted Transition Probabilities by Wife’s Birth Cohort</td>
<td>108</td>
</tr>
</tbody>
</table>
B.4 Predicted Transition Probabilities by Wife’s Birth Cohorts, Conditional on at least One Spouse Retiring ................................. 109

B.5 Predicted Transition Probabilities by Wife’s Birth Cohort ......................... 110

B.6 Predicted Transition Probabilities by Wife’s Birth Cohorts, Conditional on at least One Spouse Retiring .................................. 111

B.7 Predicted Transition Probabilities by Wife’s Birth Cohort ......................... 112

B.8 Predicted Transition Probabilities by Wife’s Birth Cohorts, Conditional on at least One Spouse Retiring .................................. 113

B.9 Predicted Transition Probabilities by Wife’s Birth Cohort ......................... 114

B.10 Predicted Transition Probabilities by Wife’s Birth Cohorts, Conditional on at least One Spouse Retiring .................................. 115

B.11 Predicted Transition Probabilities by Wife’s Birth Cohort ......................... 116

B.12 Predicted Transition Probabilities by Wife’s Birth Cohorts, Conditional on at least One Spouse Retiring .................................. 117
Chapter 1

ADOLESCENT SUBSTANCE USE AND INTERGENERATIONAL TRANSFERS: EVIDENCE FROM MICRO DATA

1.1 Introduction

The economic literature on intergenerational transfers within the family emphasizes two main competing motives for inter vivos transfers: altruism towards children (Becker (1974), Barro (1974)), and self-interested exchange between parents and children (Cox (1987), Cox and Rank (1992), Horioka (2002)). More recently, these models have been extended to account for the role played by parents in shaping their children’s preferences. Such theoretical extensions typically postulate that preferences of children are not exogenous, but are influenced by the attitudes and actions of their parents and/or other role models (see Bhatt and Ogaki (2008), Akabayshi (2006), Doepke and Zilibotti (2008), Bisin and Verdier (1998, 2001), Fernandez, Fogli and Olivetti (2004)).

Empirical evidence suggests that parents attempt to influence children during their formative years because of the correlation between childhood experiences and adult behaviors (Maital (1982)). The mechanisms that parents can use to influence child behavior can be divided into pecuniary (such as monetary rewards) or non-pecuniary (such as grounding or spanking). The use of such incentives by parents has also been well established in the literature (see Section 1.2 for a detailed discussion). However, to the best of my knowledge, there is no previous study that has
tried to estimate the direct effect of child behavior on monetary transfers that she receives from her parents. My paper adds to the literature in this regard and attempts to derive a causal estimate of the effect of child’s substance use on parental transfers.

This paper uses data from the National Longitudinal Survey of Youth, 1997 (NLSY97) to examine the relationship between parental transfers and youth substance use as measured by alcohol consumption. A key challenge in estimating this relationship is the possible endogeneity of the child’s alcohol use in the regression equation of transfers she receives from parents. For example, higher transfers will make alcohol more affordable for the child and may positively influence her likelihood to indulge in greater consumption. Hence, using ordinary least square (OLS) would yield a biased estimate of the effect of child substance use. The main contribution of my paper is to recover a causal estimate of the effect of child substance use on parental transfers by using instrumental variable estimation. The suggested instrument utilizes time as well as cross-state variation in the price of alcoholic beverages as a source of exogenous variation. This is a valid instrument as substance price is potentially uncorrelated with parental transfers but is related to the child’s likelihood of alcohol consumption (conditional on controls for the child’s education, parental income, education and family structure). The main finding of the paper is that incidence of alcohol consumption by the child significantly reduces the amount of transfers made by the parent.

One interpretation of this finding is that some parents may use pecuniary incentives to influence their children’s behavior. Thus, parents may use transfers as a signaling mechanism to influence adolescent drinking. If the child reduces drinking, then parents increase transfers sending a positive signal that such good behavior will be rewarded. On the other hand, if the child increases drinking then parents reduce transfers, signaling that such behavior is undesirable. Given that many
teenagers buy their own alcohol and allowance is an important component of their youth income, cutting down transfers in response to drinking is a credible mechanism for parents to try to control adolescent alcohol consumption. Further, since preferences and behavior are often correlated, my results can also serve as an empirical basis for the use of such mechanisms in recent theoretical models related to the role of parents in shaping their children’s preference (see section 1.5 for evidence and a discussion on this issue).

From a policy perspective, youth alcohol consumption is an important issue and many intervention programs for reducing under age drinking are being implemented in the U.S.\textsuperscript{1} In this context, my results have implications for the Family-Based Prevention Programs aimed at reducing adolescent substance use.\textsuperscript{2} Such programs typically are based on parental ability to influence their children’s substance use and involve setting clear rules against drinking, consistently enforcing these rules, and monitoring the child’s behavior to reduce the likelihood of underage drinking (Steinberg, Fletcher, and Darling (1994)). To this end, my results suggest that limiting and monitoring child allowance may reduce the chances of excessive drinking by youth and hence should be included (as an incentive mechanism) to supplement existing measures of parental monitoring in Family-Based Prevention Programs.

The rest of the paper is organized as follows. Section 1.2 presents a brief review of the literature that highlights the role of parents in shaping their children’s economic preferences. It also provides a brief discussion of existing empirical evidence on pecuniary and non pecuniary channels used by parents to influence their children’s actions. Section 1.3 summarizes the data set used for the

\textsuperscript{1}See Alcohol Alert: Underage Drinking: Why Do Adolescents Drink, What Are the Risks, and How Can Underage Drinking Be Prevented? (2006) for an excellent summary on youth alcohol consumption and intervention programs.

\textsuperscript{2}An example of such programs is the Iowa Strengthening Families Program (ISFP) which has shown long-lasting preventive effects on underage alcohol use.
analysis. Section 1.4 outlines the empirical model and estimation strategy and presents the results of the estimation exercise. Section 1.5 provides an interpretation of the empirical results and Section 1.6 concludes.

1.2 Related Literature

The empirical analysis presented in this paper is related to the literature on the use of pecuniary and non-pecuniary incentive mechanisms by parents to influence the behavior and attitudes of their children. In this section I summarize the findings in the literature on the following issues pertinent to the present discussion.

First is the role played by parents in shaping their children’s economic attitudes and preferences. One type of evidence can be found in the recent literature on cultural transmission of preferences between parents and children. For example, Dohmen, Falk, Huffman and Sunde (2008) use the German Socio-Economic Panel (SOEP) data and test for intergenerational correlation in risk and trust attitudes. One of their main findings is that children develop similar attitudes toward risk and trust as their parents. Fernandez, Fogli and Olivetti (2004) found evidence for an important role of mothers in the transmission of attitudes favoring the participation of women in the labor force to their sons. Similarly, Bisin and Verdier (2001) propose a general model with endogenous cultural transmission mechanisms wherein parents take actions to affect children’s traits, which as a special case can correspond to time preferences. In the psychology literature, there is evidence in favor of the influence of parents in the development of children’s willingness to delay rewards. For example Webley and Nyhus (2006) use the De Nederlandsche Bank Household Survey (DHS) data and find evidence to support the hypothesis that parental orientations have an effect on the economic behavior of children in their youth as well as in adulthood. They observe high degrees
of association between children’s savings and parental savings, household income and economic socialization of parents. Mischel (1961) studied children in the West Indian islands of Grenada and Trinidad and found that the children of Grenada showed greater preference for a higher delayed reward than a smaller immediate reward when compared to the children of Trinidad. He also found that this difference is driven mainly by the critical role fathers play in imparting cultural values of thrift to the children of Grenada and those of immediate gratification to the children of Trinidad.

Given the evidence above in support of parents playing a role in shaping their children’s preferences, a second related question is concerned with the channels that are used by parents to influence their children’s behavior. Parents can motivate their children through pecuniary and/or non-pecuniary incentives. Using data from the Child Development Supplement (CDS) of the Panel Study of Income Dynamics (PSID), Weinberg (2001) finds that parents’ ability to mold their children’s behavior through pecuniary incentives is limited at low incomes leading to increased reliance on non-pecuniary mechanisms such as corporal punishment. Wauchope and Straus (1995) find that 97 percent of 3-year olds, 50 percent of 13 to 14-year olds, and one-third of 15 to 17-year olds are corporally punished in the course of a year. Surveys by Bronfenbrenner (1958) and Erlanger (1974) also find strong evidence of a negative relationship between socioeconomic status and corporal punishment. Similarly, Straus and Donnelly (1993) report that the frequency of corporal punishment declines with socioeconomic status. Sears, Maccoby, and Levin (1976) document the pervasiveness of pecuniary rewards and find that 47 percent of parents often use tangible rewards to motivate their young children while only 12 percent of parents never use tangible rewards.
1.3 Data

The empirical analysis is based on data from the NLSY97 which is a nationally representative annual survey of youths aged 12 to 16 years old as of December 31, 1996. It provides longitudinal data on demographics, income, assets, substance use, education, family structure and community backgrounds. In addition, a rich set of information relating to parental background such as income and education was collected from the parent of each youth in the first wave administered in 1997. The information on state of residence is taken from the restricted use NLSY97 Geocode data. I use the first seven waves of the survey covering years 1997 through 2003.3

Sample Selection

The NLSY97 surveyed 8,984 youths in 1997. I restrict my sample to observations with non-missing data on key variables of interest- the amount of parental transfers and substance use measured by alcohol consumption of the youth. I also restrict attention to youths with non-missing data on demographic and family structure variables such as parent’s education, number of children in the household and whether the youth lives in an urban area. Finally, since the objective is to study how parental transfers are affected by the child’s substance use, I restrict my sample to youths who are in the age range 12-18 years and co-habit with at least one parent as they are more likely to be dependent on parental transfers/allowances. This leads to a sample of 3,063 youths contributing 8,859 youth-year observations which is used to estimate the relationship between the amount of transfers and drinking behavior of the child.

3From 2004, the NLSY97 ceased to collect information on the amount of allowances received by the respondent from parents. Hence, I restrict my sample to the first seven waves of the survey.
Table 1.1 describes the unweighted sample means of the key variables of interest. Mean real parental transfers are $611. For the drinking outcome, I am interested in a measure that captures the intensity of adolescent alcohol use since the detection of such consumption by parents is higher for more intensive behavior. I define an indicator variable that takes value 1 if the respondent reports drinking five drinks or more per day on more than one occasion in the past 30 days, and 0 otherwise. In my sample, about 19 percent of youths report such a consumption pattern. Roughly 54 percent of the sample consists of males, the average age is about 16 years and 71 percent of youths are white. With regards to family characteristics, 70 percent of youths reside in an urban area and on average there are 2 children aged 18 or less in the family. Further, about 35 percent have fathers with a high school degree and 45 percent have fathers with some college and college degree.

To impute family income, I assume that family income has two parts, one that can be explained by demographic characteristics of the household and the other that follows a stochastic process. The stochastic process in turn is made up of two components, namely, permanent and transitory incomes. A shock to permanent income is expected to affect the household’s income over its lifetime, while a shock to transitory income is expected to affect the household’s income for one period. Formally the family income process is given by,

\[ Y_{it} = Z_{it}\phi + \nu_{it} \]

\[ \nu_{it} = \mu_i + \eta_{it} \]

4 I deflate all nominal variables by the implicit GDP deflater to express them in terms of 2000 dollars.

5 The National Institute on Alcohol Abuse and Alcoholism [NIAAA] defines binge drinking as a pattern of drinking alcohol that brings blood alcohol concentration [BAC] to 0.08 grams percent or above. For the typical adult, this pattern corresponds to consuming five or more drinks [men], or four or more drinks [women], in about 2 hours. In this regard, my variable which is based on binge drinking by the respondent on more than one occasion in the last one month further increases the likelihood of detection by parents, thus making a more legitimate case for parental response.
where $Y$ denotes family income and the subscripts $i$ and $t$ denote household and time, respectively. $Z$ is a vector of household demographic characteristics, $\nu$ is stochastic family income and $\mu$ denotes permanent income which for simplicity I assume manifests itself as a fixed effect. Finally, $\eta$ denotes the transitory income shock and is assumed to be independently, identically and normally distributed with zero mean.

I estimate the income process outlined above by using indicator variables for family demographic characteristics such as race, parental education level and urban residence, and a continuous variable measuring the size of the household. The resulting predicted real family income is then used to impute family income for respondents for whom it is reported missing. From Table 1, it can be observed that the mean imputed family income (in 2000 dollars) is $66,649$.  

1.4 How Youth Substance Use Affects Parental Transfers?

A Conceptual Framework

Assuming transferable utilities, Becker’s Rotten Kid Theorem posits that a parent can influence his child by specifying transfers as a function of the child’s behavior (Becker 1974, 1991). In a static framework, we can model parent-child interactions as a two stage game. In stage 1, the child maximizes his utility $U(C_k, d)$ by choosing optimal values of a consumption good $C_k$ and indulgence in substance use, $d$, where $d=1$ implies engagement in substance use. I assume for simplicity that the only source of income for the child is transfers she receives from the parent, denoted by $T$. In stage 6

\[ \text{The mean of actual real family income based on non-missing family income data (not reported in the table) is $65,299$. The correlation coefficient between the predicted family income and the actual family income is 94 percent.} \]
<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
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<td>Transfers (in 2000 Dollars)</td>
<td>$611</td>
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<tr>
<td>Indicator Variable for Drinking</td>
<td>18.5%</td>
</tr>
<tr>
<td><strong>Youth’s Characteristics</strong></td>
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<tr>
<td>Youth’s Age</td>
<td>16.3</td>
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<td>Youth’s Highest Grade Completed</td>
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<tr>
<td>Male</td>
<td>53.8%</td>
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<tr>
<td>White</td>
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<tr>
<td><strong>Family Characteristics</strong></td>
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<tr>
<td>Urban Residence</td>
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</tr>
<tr>
<td>Number of Children under 18</td>
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<td>Residential Father’s Education:</td>
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<tr>
<td><em>HS Dropout</em></td>
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</tr>
<tr>
<td><em>HS Graduate</em></td>
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<tr>
<td><em>Some College</em></td>
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<tr>
<td><em>College Graduate</em></td>
<td>23.6%</td>
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<tr>
<td>Imputed Family Income</td>
<td>$66,649</td>
</tr>
<tr>
<td>(in 2000 Dollars)</td>
<td></td>
</tr>
<tr>
<td>Number of Observations (Youth-Year)</td>
<td>8,859</td>
</tr>
</tbody>
</table>

Table 1.1: Sample means in the NLSY97 (1997-2003)
2, an altruistic parent chooses $T$ by maximizing the utility he derives from his own consumption $C_p$ and the utility level attainable by the child: $W(U_p(C_p), U_k(C_k, d))$. This choice is subject to the budget constraint $C_p \leq Y_p - T$ where $Y_p$ denotes the parent’s exogenous income. Solving the parent’s problem will give us the optimal transfer function $T^* = f(Y_p, d)$.

Econometric Model

Based on the conceptual framework discussed above, I assume that the transfers received by the child can be expressed as the following equation:

$$\text{Transfer}_{ijt} = \beta_1 + \beta_2 d_{ijt} + \beta_3 X_{ij} + \beta_4 Z_{ijt} + \theta_j + \delta_t + \epsilon_{ijt}$$  \hspace{1cm} (1.1)

where $i$ indexes individuals; $j$ indexes states; and $t$ indexes years. $\text{Transfer}$ is log real transfers received by the child from parents. $d$ measures drinking intensity and as defined earlier, is an indicator variable that takes value 1 if the respondent reports drinking five drinks or more per day on more than one occasion in the past 30 days, and 0 otherwise. $X$ denotes a vector of time invariant variables that can affect transfers such as parental education, race and gender of the youth. $Z$ denotes a vector of time varying explanatory variables such as education of the youth, family income, number of children under 18 in the family and an indicator variable for whether the youth lives in an urban area. Finally, $\theta$ and $\delta$ are vectors of state and time fixed effects, respectively.

The parameter of interest is $\beta_2$. If parents use transfers to punish undesirable behavior then we will expect a negative relationship between substance use and transfers; $\beta_2 < 0$. However, estimation by OLS will yield biased parameter values since substance use of the child is plausibly endogenous. For example, the child’s alcohol consumption in all likelihood will be affected by how much money he/she has, which in turn will depend on the amount of parental transfers. To
account for the endogeneity of substance use I estimate equation (1.1) by using instrumental variable (IV) estimation.

Estimation Strategy

I use cross state and time series variation in the price of the substance as a source of exogenous variation that affects substance use of the youth.\textsuperscript{7} This is a valid instrument as it is reasonable to expect no direct effect of substance prices on parental transfers. At the same time, a strong correlation between substance use of the child and price in data has been well documented in many studies measuring the responsiveness of youth substance use to price of the substance.\textsuperscript{8}

In the regression specified in equation (1.1) we have an endogenous indicator variable measuring substance use by the child. The standard two stage procedure used in IV estimation will produce consistent parameter estimates as consistency of the Two Stage Least Squares (2SLS) estimators is not affected by the presence of binary endogenous regressors (Wooldridge (2002)). However, it will lead to biased standard errors making the estimates less precise. I use the procedure described in Wooldridge to correct the standard errors. Specifically, I estimate the first stage

\textsuperscript{7}I use the price of beer as the relevant substance price since beer is commonly accepted as the preferred alcoholic beverage for youths. This state level price data is taken from “Statewide Availability Data System II: 1933 - 2003” by Ponicki, W. R. (2004), National Institute on Alcohol Abuse and Alcoholism Research Center Grant P60-AA006282-23, Berkeley, CA: Pacific Institute for Research and Evaluation, Prevention Research Center.

\textsuperscript{8}Carpenter (2008) using repeated cross-section data from the national, state, and local Youth Risk Behavior Surveys over the period 1991-2005 found that a one-dollar increase in the excise tax per cigarette pack (which serves as a proxy for price) reduces smoking participation by 3-6 percentage points which translates into price elasticities of smoking participation for high school youths in the range -0.23 to -0.56. Grossman (2004) found that changes in price can explain a good deal of the observed changes in cigarette smoking, binge alcohol drinking, and marijuana use by high school seniors. He found that the 70 percent increase in the real price of cigarettes since 1997 explains most of the reduction in the cigarette smoking participation rate since that year. Further, a 7 percent increase in the real price of beer between 1990 and 1992 due to the Federal excise tax hike on that beverage in 1991 accounts for almost 90 percent of the 4 percentage point decline in binge drinking in that period.
equation as a Probit by maximum likelihood and obtain the fitted probability of substance use. I then estimate equation (1.1) by the IV method using the predicted probabilities of substance use as an instrument for the child’s substance use.9

The two stage estimation procedure is outlined below:

Stage 1: Estimate substance use by the child as a Probit model. Formally, the first stage regression is given by,

\[ Pr[d_{ijt} = 1 | \Omega_{ijt} = \omega_{ijt}] = \Phi(\omega_{ijt}' \delta) \]  

(1.2)

where \( \Omega_{ijt} = (X_{ij}, Z_{ijt}, P_{jt})' \) is a vector of explanatory variables affecting the probability of substance use by the child. \( P_{jt} \) denotes the price of the substance in state \( j \) and period \( t \).

The identifying assumption is that while \( X_{ij} \) and \( Z_{ijt} \) enter both the first and second stage regressions, \( P_{jt} \) only enters the first stage regression.

Stage 2: Using the predicted value from the first stage, estimate equation (1.1) by IV using instruments \( \hat{d}_{ijt}, Z_{ijt} \) and \( X_{ij} \).

There are many advantages to this approach. First, it takes the binary nature of the endogenous variable into account. While the two-stage least squares (2SLS) consistency of the second stage does not hinge on getting the functional form right in the first stage (Angrist and Krueger (2001)), 2SLS leads to biased estimates in finite samples and it is not known how misspecification of functional form in the first stage may affect this bias. Second, it does not require the binary response

9Note that this procedure is different from the “pseudo-IV” procedure of simply replacing child’s substance use in (1.1) with the predicted value of child’s substance use from the Probit and estimating the resulting equation by OLS. Here consistency is not guaranteed unless the first stage is correctly specified, and the standard errors need to be adjusted.
model of the first stage to be correctly specified. Third, although the instruments used are generated from Probit, the standard IV standard errors are still asymptotically valid (see Wooldridge p. 623, procedure 18.1). Finally, the above procedure provides estimates that are more efficient than those obtained from a standard 2SLS procedure.¹⁰

In my data, since variation in the instrumental variable (price of the substance) is only across state and year cells, I correct standard errors for within state-year cell correlations in the error term.¹¹

Estimation Results

In this section I present the main results of my empirical exercise. To ensure that the reported results are robust, I estimate four different specifications identified by the differing treatment of

¹⁰(i) A caveat to the IV estimation strategy outlined in the paper is that in equation (1) due to lack of data, we cannot directly control for parental substance use which may be relevant in determining the child’s substance use and hence the amount of parental transfers. Hence, omitting this variable will lead to a biased estimate of \( \beta_2 \). However, it can be shown that the IV estimate of \( \beta_2 \) is biased upwards. To see this, consider a regression equation given by

\[
\text{Transfer}_{ijt} = \alpha (\text{Child’s Substance Use})_{ijt} + \epsilon_{ijt}
\]

Then the omitted variable bias of the IV estimator of \( \alpha \) caused by ignoring parental substance use is:

\[
\text{plim}(\hat{\alpha}_{IV} - \alpha) = \gamma \frac{\text{Cov}(P_{jt}, \text{Parent’s Substance Use}_{ijt})}{\text{Cov}(P_{jt}, \text{Child’s Substance Use}_{ijt})}
\]

where the instrument \( P_{jt} \) is price in state \( j \) and year \( t \). Now both the parent and the child’s substance use are inversely related to the price. Hence the sign of the above expression depends on the sign of \( \gamma \) which captures the effect of parental alcohol consumption on transfers. It is reasonable to argue that this relationship is negative due to the budget constraint of the parent—the more he spends on his drinking, the less is the money available to transfer to the child. Hence, \( \gamma < 0 \) which implies \( \text{plim}(\hat{\alpha}_{IV} - \alpha) < 0 \). Since we expect \( \alpha \) to be negative, this suggests that \( \hat{\alpha}_{IV} \) is biased upwards.

(ii) Note that there may be other omitted variables in regression (1). However, as long as these are uncorrelated with the instrument (price of beer) they pose no problem for the analysis presented in the paper.

¹¹In the literature on the price responsiveness of youths substance use there is a concern that if alcohol manufacturers employ any state-specific pricing then prices may be endogenous to alcohol consumption. To address this issue, I also estimate equation (1.1) using state-level tax data as an instrument. The outcome of this exercise is not reported but is available upon request. The main results of the paper remain qualitatively unchanged and we find a large negative effect of alcohol consumption on parental transfers.
period and state effects in equation (1.1). The specification under Column (1) of each Table contains no controls for time period and state effects; Column (2) parameterizes the period effect by a linear trend but includes no control for state-specific effects; Column (3) includes a linear time trend and state-fixed effects; and finally Column (4) contains the full set of state and year dummies to account for state-specific and period-specific fixed effects.

Probit and first stage results are summarized in Tables 1.2 and 1.3 respectively. From Table 1.2 we see that the proposed instrument (price of alcohol) is statistically significant in the equation of child’s substance use and consistent with our intuition is negatively related to child’s drinking variable. From Table 1.3 we find that predicted child’s drinking is statistically significant with a First-Stage Staiger and Stock (1997) F Statistic greater than 10 across all specifications. Thus, I conclude that my instrument not only moves the child’s drinking variable in the predicted direction, but also that my specifications do not appear to suffer from problems associated with weak instruments.12

Note that I am using a non linear first stage to generate predicted substance use of the child as an instrument. There is always a question of how much of my identifying variation is coming from my instrument (price of alcohol) and how much is simply a manifestation of the non linearity in the first stage. While there is no easy way of answering this question, based on a private conversation with Jeffrey Wooldridge, one really needs to look at the coefficient of the instrument in the Probit estimation. If it is not significant it is very unlikely the Probit fitted values are an appropriate instruments and most likely this estimation strategy will simply be exploiting the nonlinearity in the Probit fitted values. Since in Table 1.2 the coefficient on alcohol price (across all specifications) is statistically significant, it give me some faith in my estimation strategy being not completely driven by implicit non-linearity in the Probit fitted values.12
## Table 1.2: Probit MLE Results

<table>
<thead>
<tr>
<th>Dependent Variable: Indicator Variable for Drinking ($d$)</th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price of Beer -0.107** (in 2000 Dollars)</td>
<td>(0.065)</td>
<td>(0.068)</td>
<td>(0.066)</td>
<td>(0.057)</td>
</tr>
<tr>
<td>Highest Grade Completed 0.072*</td>
<td>(0.03)</td>
<td>(0.051)</td>
<td>(0.051)</td>
<td>(0.055)</td>
</tr>
<tr>
<td>Urban Residence 0.02</td>
<td>(0.043)</td>
<td>(0.043)</td>
<td>(0.041)</td>
<td>(0.039)</td>
</tr>
<tr>
<td>No. of Children Aged &lt; 18 -0.097*** (in 2000 Dollars)</td>
<td>(0.015)</td>
<td>(0.016)</td>
<td>(0.016)</td>
<td>(0.017)</td>
</tr>
<tr>
<td>Log Imputed Family Income 0.007</td>
<td>(0.022)</td>
<td>(0.022)</td>
<td>(0.022)</td>
<td>(0.022)</td>
</tr>
<tr>
<td>Constant -0.863</td>
<td>(0.498)</td>
<td>(0.587)</td>
<td>(0.58)</td>
<td>(0.586)</td>
</tr>
<tr>
<td>Linear Time Trend - Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>Region Fixed Effects - No.</td>
<td>-</td>
<td>-</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Time Fixed Effects - No.</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>8859</td>
<td>8859</td>
<td>8859</td>
<td>8859</td>
</tr>
<tr>
<td>Pseudo-$R^2$</td>
<td>0.055</td>
<td>0.0619</td>
<td>0.0662</td>
<td>0.082</td>
</tr>
<tr>
<td>Log-Likelihood</td>
<td>-4008</td>
<td>-3979</td>
<td>-3960</td>
<td>-3894</td>
</tr>
</tbody>
</table>

*** p<0.001, ** p<0.01, * p<0.05

1. Standard errors are corrected for state/year clustering.
2. Coefficient estimates of only select covariates are presented in the table.
3. Each specification includes controls for race, gender, and parental education.
<table>
<thead>
<tr>
<th></th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Predicted Probability of Drinking ((\hat{d}))</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1.897***</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>(0.266)</td>
<td>(0.225)</td>
<td>(0.23)</td>
<td>(0.23)</td>
</tr>
<tr>
<td><strong>Predicted Probability of Drinking ((\hat{d}))</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>2.020***</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>(0.225)</td>
<td>(0.225)</td>
<td>(0.23)</td>
<td>(0.23)</td>
</tr>
<tr>
<td><strong>Predicted Probability of Drinking ((\hat{d}))</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
<td>1.949***</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>(0.23)</td>
<td>(0.23)</td>
<td>(0.23)</td>
<td>(0.23)</td>
</tr>
<tr>
<td><strong>Predicted Probability of Drinking ((\hat{d}))</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>1.419***</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>(0.264)</td>
</tr>
<tr>
<td><strong>Constant</strong></td>
<td>-0.161*</td>
<td>-0.192**</td>
<td>0.515</td>
<td>0.164</td>
</tr>
<tr>
<td></td>
<td>(0.078)</td>
<td>(0.07)</td>
<td>(0.317)</td>
<td>(0.213)</td>
</tr>
<tr>
<td><strong>Linear Time Trend</strong></td>
<td>-</td>
<td>Yes</td>
<td>Yes</td>
<td>-</td>
</tr>
<tr>
<td><strong>State Fixed Effects</strong></td>
<td>-</td>
<td>-</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td><strong>Time Fixed Effects</strong></td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>Yes</td>
</tr>
<tr>
<td><strong>Observations</strong></td>
<td>8859</td>
<td>8859</td>
<td>8859</td>
<td>8859</td>
</tr>
<tr>
<td><strong>Stock and Staiger F- Statistic</strong></td>
<td>51</td>
<td>80.33</td>
<td>71.49</td>
<td>28.84</td>
</tr>
<tr>
<td><strong>Shea Partial (R^2) of Excluded Instrument</strong></td>
<td>0.01</td>
<td>0.0164</td>
<td>0.0154</td>
<td>0.0102</td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.057</td>
<td>0.069</td>
<td>0.08</td>
<td>0.089</td>
</tr>
</tbody>
</table>

*** p<0.001, ** p<0.01, * p<0.05

1. Standard errors are corrected for state/year clustering.
2. Coefficient estimates of only select covariates are presented in the table.
3. Each specification includes controls for gender, race, family size, child’s education, parental education, urban residence, and family income.

Table 1.3: First Stage Estimates
Table 1.4 presents the second stage estimation results. The dependent variable is the logarithm of parental transfers in 2000 prices. I control for family structure as measured by the number of children less than 18 years of age and urban residence as well as demographic variables such as the child’s education, race and education of the father.\(^{13}\)

In all specifications, as expected, a greater number of children in the family lowers transfers because they compete for a fixed amount of parental resources. Urban residence increases the amount of transfers received which can be interpreted as capturing the wealth effect assuming that urban households have more resources than rural households. Also, as expected, higher (imputed) family income increases the amount of transfers received by children.

The main finding of interest is that after accounting for the endogeneity of substance use, alcohol consumption reduces parental transfers to the child and this effect is statistically significant at all conventional levels of significance. As observed, the size of the effect is quite large and I report the effect of drinking on transfers as a proportionate change in Panel B of Table 2.\(^{14}\) The magnitude of the effect ranges from 80-90 percent depending on how we account for time and/or state effects.

One way to interpret these large percentage changes in transfers is to argue that a parent who does

\(^{13}\) All the reported regression results are robust to alternative controls for individual and family characteristics. For example, in one specification (not reported) I included both parents’ education categories, age of the respondent and the number of children under 6 years of age in the household. I found qualitatively similar results.

\(^{14}\) These proportionate changes are computed from the estimated regression coefficient for substance use in Table 1.4. Suppose, we have the following regression equation:

\[
\ln(Y_i) = \beta_0 + \beta_1 D_i + \epsilon_i
\]

where \(D_i\) is a dummy variable. Then, the estimated proportionate change in \(Y_i\) due to the change in the dummy variable value from 0 to 1 is given by:

\[
e^{\hat{\beta}_1} - 1
\]

The standard error for this expression can be computed by using the Delta Method.
### Table 1.4: Second Stage Estimates

actively use monetary channels to punish the child’s substance use will in all probability try to cut the child off from the source and hence respond by reducing her transfers substantially.

### 1.5 Why do parents react to children’s substance use by reducing transfers?

One way to rationalize the negative effect of the child’s alcohol consumption on parental transfers is to think along the lines of the child’s preference shaping theory in which parents use different
mechanisms to influence child behavior. It is reasonable to assume that alcohol consumption can induce changes in the child’s behavior unacceptable to a loving parent. In some cases, the parent acting with the long run benefit of the child in mind may resort to influencing child behavior in the short run through lowering monetary transfers.\textsuperscript{15}

An important factor affecting the economic behavior of the child is the rate of time preference. Individuals exhibit differences in the extent to which they discount future rewards. This issue has been dealt with rigorously in the experimental economics and psychology literature. The standard approach taken is to have participants make repeated choices between hypothetical money amounts available over a wide range of delays in a controlled setting. Using this approach, a robust finding is that substance abusers exhibit greater degrees of temporal discounting than non-abusers (Bickel and Marsch (2001)). Specifically, a lower discount factor is found to be correlated with smoking, drinking and use of illegal drugs (Ida and Goto (2009), Vuchinich and Simpson (1998), Madden et al. (1997), Bicket et al. (1999)). While most studies document a robust negative correlation between youth substance use and the discount factor, whether greater discounting and shorter time horizons are a cause or a consequence of substance abuse is open to debate. For example, one can argue that a lower discount factor leads to greater substance use among children. Using data on adolescent and young-adult smokers, Reynolds (2004) found support for the hypothesis that a high rate of cigarette consumption is related to a lower discount factor, rather than the alternative hypothesis that smokers are predisposed with a lower discount factor. To summarize, without any

\textsuperscript{15}Note that the above interpretation is based on the assumption that parents act to influence child behavior driven by altruism. A caveat to this discussion is the extreme case of parent-child exchange models where the parent on aging hopes to be cared for by the child. This kind of framework has been examined by Cox (1987) and other researchers in the literature on the motives behind intergenerational transfers. In such models the parent may not be trying to influence child substance use behavior but may simply be taking the behavior as given. The substance abuse signals that the child is less likely to provide effectively for the parent at old age and thus may induce the parent to reduce transfers. In such a setting, altruism-based interpretations of my results might not hold in entirety.
attempt to assign the direction of causality, there seems to be robust evidence for a negative correlation between substance use by youth and their discount factor.

Given the evidence above, an interesting application of the results presented in this paper is to think of them as providing an empirical motivation for parent-child interaction models where parents use monetary incentives to influence economic behavior of their children. One such scenario is captured in the notion of tough love altruism suggested by Bhatt and Ogaki (2008). They focus on the role of the parent in molding the time preference of the child and develop a Tough Love Model of Intergenerational Altruism. In the standard altruism model proposed by Becker (1974) and Barro (1874) the current generation derives utility from its own consumption and the utility level attainable by its descendant. Bhatt and Ogaki model tough love by modifying the standard altruism model in two ways. First, the child’s discount factor is endogenously determined, so that low consumption at young ages leads to a higher discount factor later in her life. Second, the parent evaluates the child’s lifetime utility with a constant high discount factor. The tough love altruism model predicts that transfers from the parent will fall when the child’s discount factor falls. This is in contrast with the predictions of the standard altruism model that transfers from parents are independent of exogenous changes in the child’s discount factor. Since exogenous changes in the child's discount factor that make him impatient are likely to cause behavior which calls for the parent’s corrective actions, the tough love altruism model is more consistent with empirical evidence on parental punishments as well as the role of parents in shaping children’s preferences as compared to the standard altruism model.
1.6 Conclusion

The role of parents in shaping children’s economic preferences and attitudes has been increasingly utilized in many recent theoretical contributions. An important issue in this context is the different kinds of channels used by parents to achieve this goal. This paper attempts to study parent-child interactions by examining the relationship between child substance use and parental transfers. Using the first seven waves of the NLSY97, I estimate the effect of alcohol consumption by children on the amount of parental transfers. One of the main challenges in identifying this effect is the potential endogeneity of the child’s substance use. I account for this by exploiting time series and cross-state variation in substance prices as a source of variation exogenous to the amount of transfers made by parents to their children. Based on the IV estimates, incidence of alcohol consumption by the child significantly reduces the amount of parental transfers in the NLSY97 sample.

One way to interpret this result is to imagine an altruistic parent using pecuniary incentives to influence child behavior through signaling. Higher transfers in response to lower drinking sends a positive signal that such good behavior will be rewarded. On the other hand, if the child increases drinking then parents reduce transfers, signaling that such behavior is undesirable. Given that many teenagers buy their own alcohol and allowance is an important component of their income, cutting down transfers in response to drinking is a credible mechanism for parents to try to control adolescent alcohol consumption. From a policy perspective, limiting and monitoring pocket money combined with other forms of parental monitoring may increase the efficacy of Family-Based Prevention Programs aimed at reducing the chances of excessive drinking by youth.
Chapter 2

TOUGH LOVE AND INTERGENERATIONAL ALTRUISM

2.1 Introduction

How different generations are connected is an important economic issue with implications for individual economic behavior such as, savings, investment in human capital, and bequests, which in turn affect aggregate savings and growth. These interactions are important from a policy perspective as well since they determine how families respond to public policies aimed at redistributing resources among family members. A commonly used paradigm to study such linkages is the standard altruism model proposed by Becker (1974) and Barro (1974) in which the current generation derives utility from its own consumption and the utility level attainable by its descendant. Using this framework, Barro found that there will be no net wealth effect of a change in government debt.

A striking prediction of the standard altruism model is that when the child becomes impatient, transfers from the parent to the child do not change when the child is borrowing constrained (as we will show in Section III). This implication of the model is not consistent with recent empirical evidence on pecuniary and non-pecuniary parental punishments (see Weinberg (2001), Hao, Hotz, and Jin (2008), and Bhatt (2010) for empirical evidence). For example, imagine that a child befriends a group of impatient children and suddenly becomes impatient because of their influence. As a result, the child starts to spend more time playing with the new friends and less time studying.
In the worst cases, the child starts to smoke, drink, or consume illegal drugs (see Ida and Goto (2009) for empirical evidence that shows association of low discount factor and smoking). At least some parents are likely to respond by pecuniary punishments, such as lowering allowances, or non-pecuniary punishments, such as grounding. Another feature of the standard altruism model is that it precludes parents from directly influencing their child’s time preferences. However, there is empirical evidence that parents attempt to shape their children’s economic behavior and attitudes, including time preferences, as reviewed below. In many recent theoretical contributions, preferences of children are not exogenous, but are shaped by the attitudes and actions of their parents and other role models. For example, in the literature on cultural transmission of preferences, Bisin and Verdier (2001) proposed a general model with endogenous cultural transmission mechanisms wherein parents take actions to affect children’s traits, which as a special case can correspond to time preferences. In some other models, even though parents do not take actions with a deliberate intention to affect their children’s preferences, they end up doing so indirectly. For example, Fernandez, Fogli and Olivetti (2004) used a dynamic model where mothers who work play an important role in the transmission of attitudes favoring the participation of women in the labor force to their sons. We will further discuss this issue by presenting empirical evidence for parents’ role in children’s endogenous preference formation in the next section.

The main contribution of this paper is to propose a new theoretical model of parent-child interaction that incorporates a mechanism through which parents can affect their children’s time preference formation. We develop a Tough Love Model of Intergenerational Altruism, in which the parent is purely altruistic to the child, but exhibits tough love: he allows the child to suffer in the short run with the intent of helping the child in the long run. In contrast to the prediction of the standard altruism model that transfers are independent of exogenous changes in the child’s discount factor, our tough love altruism model predicts that transfers from the parent will fall when the
child’s discount factor falls. An interpretation of this result is that parents with the tough love motive use pecuniary incentives to mold their children’s time preferences. Since exogenous changes in the child’s discount factor that make him impatient are likely to cause behavior that calls for the parent’s corrective actions, the tough love altruism model is more consistent with empirical evidence on parental punishments as well as the role of parents in shaping children’s preferences as compared to the standard altruism model.

In the simple setting of a three period economy with a single parent and single child with perfect information and borrowing constraints, we model parental tough love by combining the two ideas that have been studied in the literature in various contexts. First, the child’s discount factor is endogenously determined, so low consumption at a young age leads to a higher discount factor later in her life. This is based on the endogenous discount factor models of Uzawa (1968), except that the change in the discount factor is immediate in Uzawa’s formulation whereas a spoiled child with high consumption progressively grows to become impatient in our formulation.\(^\text{16}\) Second, the parent evaluates the child’s lifetime utility with a constant discount factor that is higher than that of the child. Since the parent is the social planner in our simple model, this feature is related to recent models in which the discount factor of the social planner is higher than that of the agents.\(^\text{17}\) In our model, these two features lead the parent to exhibit tough love behavior in which he takes into account the influence of income transfers to the child on the latter’s discount factor.

An argument for the plausibility of endogenous discounting can be found in Becker and Mulligan (1997). They model an individual whose discount factor depends on the remoteness or vividness of imagined future pleasures. Becker and Mulligan’s model involves investment in human capital to increase the vividness of the imagination. For the direction of the effect of wealth on the

\(^{16}\text{Recent theoretical models that adopt the Uzawa-type formulation include Schmitt-Grohé and Uribe (2003) and Choi, Mark, and Sul (2008).}\)

\(^{17}\text{See Caplin and Leahy (2004), Sleet and Yeltekin (2005), (2007), Phelan (2006), and Farhi and Werning (2007).}\)
This paper focuses on the parent’s role in preference formation. A related work is Mulligan’s (1998) work on the altruistic preference formation of the parent toward the child.
factor. In this paper, we are emphasizing the role of the parent in molding the time preference of the child. In this regard, our model is closely related to Akabayashi (2006) and Doepke and Zilibotti (2008). In these models also the parent takes actions in order to affect the child’s discount factor. In Akabayashi’s model, the child has endogenous discounting, and the parent evaluates the child’s lifetime utility with a fixed discount factor. Together with asymmetric information about the child’s ability, Akabayashi’s model can explain abusive repeated punishments by parents under certain parameter configurations. In Doepke and Zilibotti’s model, the parent uses the child’s discount factor to evaluate the child’s lifetime utility. They use their model of occupational choice to account for a number of observations about the British Industrial Revolution. The main difference from our model is that these authors adopt a Becker-Mulligan type formulation of endogenous discounting so that the child becomes more patient when her human capital is higher. In contrast, we adopt an Uzawa-type formulation for our model.

The remainder of the paper is organized as follows. Section 2.2 reviews the empirical evidence related to the key assumptions of the tough love model. Section 2.3 explains the structure and main findings of our model with only a consumption good and contrasts the implications of the model with those of the standard altruism model. Section 2.4 proposes two alternative models of altruism in order to show that both features discussed above (endogenous discount factor of the child and the parent’s evaluation with a high discount factor) are necessary in order for transfers to decrease when the child exogenously becomes impatient for a wide range of parameters. Section 2.5 discusses whether or not there is a sense in which the child is indeed better off with tough love. Section 2.6 introduces leisure in the tough love altruism model with the objective of studying how parental transfers are affected by endogenous changes in the child’s income caused by (exogenous) changes in her discount factor. Section 2.7 concludes.
2.2 A Review of Empirical Evidence

In this section, we review empirical evidence related to the key assumptions in the tough love model.

Our first question is whether or not there is empirical evidence for parents’ behavior influencing their children’s discount factors as well as other economic preferences and attitudes. A necessary condition for parents’ behavior to be able to affect children’s time discounting factors is that genetic factors do not completely determine time discounting. Using a unique data set of twins in Japan, Hirata et al (2009) found empirical evidence in favor of this condition. Knowles and Potslewaite (2005) used data from the PSID to examine the relationship between parental attitudes toward planning for the future and their children’s saving rates. They found that that for the oldest children, the parents’ attitudes explain a third of the variance in savings rates that remains after controlling for income and demographics. In the psychology literature, there is evidence in favor of the influence of parents in the development of children’s willingness to delay rewards. Mischel (1961) studied children in the West Indian islands of Grenada and Trinidad. He found that the children of Grenada showed a greater preference for a higher reward later than a smaller immediate reward compared to the children of Trinidad. He also found that this difference is driven mainly by the critical role fathers played in handing down cultural values of thrift to the children of Grenada and those of immediate gratification to the children of Trinidad. Recent literature on cultural transmission of preferences between parents and children also provides evidence for the effect of parents’ actions on a child’s economic attitudes and behavior. For example, Dohmen et al (2008) used German Socio-Economic Panel (SOEP) data and tested for intergenerational correlation in risk and trust attitudes. One of their main findings is that children develop similar attitudes toward risk and trust as their parents. Fernandez, Fogli and Olivetti (2004) found evidence for an important role of mothers in the transmission of attitudes favoring the participation of women in
the labor force to their sons. Finally, we can also draw evidence from the empirical literature on skill formation. Cunha et al (2006) divide skill formation into that for cognitive skills and that for non-cognitive skills. Non-cognitive skills include patience and time preferences. One of their main findings pertinent to the present discussion is that ability gaps in both cognitive and non-cognitive skills across individuals and across socioeconomic groups are strongly correlated with parental education and maternal ability.

Our second question is whether or not there is direct empirical evidence that some parents take actions with an intention to affect children’s behavior. This issue has been addressed more directly in the psychology literature than in the economics literature. Baumrind (1966) identified three modes of parental control. The first mode is permissive where the parent acts as a resource to the child and does not actively involve himself in shaping the current and future behavior of the child. The second mode is authoritarian where the parent uses a set standard of conduct that is theologically or religiously motivated and tries to shape and control the child’s behavior with overt use of power. The third mode is authoritative where the parent actively involves himself in shaping the child’s behavior and attitudes and uses reasoning and discipline to ensure a well-rounded long run development of the child. He affirms the child’s current behavior, separating right from wrong, and also sets standards for the child’s future behavior. Carlson and Grossbart (1988) used survey data on the mothers of schoolchildren (kindergarten through sixth grade) and divided them into groups based on the parenting style starting from neglecting all the way to rigidly controlling. They found evidence suggesting that authoritative parents grant less consumption autonomy to their children, have greater communication with their children about consumption related issues, set higher consumer socialization goals and exhibit greater monitoring of children’s consumption vis-a-vis both permissive and authoritarian parents. More recently Webley and Nyhus (2006) used De Nederlandsche Bank household survey (DHS) data and found evidence to support the hypothesis
that parental orientations affect the economic behavior of their children in both childhood and adulthood. In Webley and Nyhus’ analysis, they observed high degrees of association between children’s savings and parental savings, household income and economic socialization of parents.

Since an important assumption of the tough love model is endogenous discounting, we review empirical evidence for endogeneity of the discount factor in this section. In the literature there are two competing hypotheses that allow for endogenous discount factor by linking patience to wealth. First is the Fisher’s hypothesis that the rich are more likely to be patient. Second is the Uzawa’s hypothesis that implies discount factor is decreasing in wealth. Becker and Mulligan (1997) cite empirical evidence for endogenous discounting consistent with the Fisher’s hypothesis.

However, it is necessary to be careful in evaluating the empirical evidence for endogenous discounting because of two problems. First, we have the endogeneity problem in that patient people with high discount factors tend to accumulate financial and human wealth. Thus we may find that rich people have higher discount factors than poor people even when the discount factor of an individual is decreasing in wealth as in Uzawa’s model. Second, endogenous discounting and wealth-varying intertemporal elasticities of substitution (IES) (see Atkeson and Ogaki (1996)) can have similar implications in growing economies, and may be hard to distinguish from one another.

The endogeneity problem mentioned above is addressed in Ikeda, Ohtake, and Tsutsui (2005). In their paper, they found that without accounting for the possible endogeneity between discount factors and wealth the discount factor appears to be an increasing function of income/wealth. After taking in to account the endogeneity problem, they find evidence in favor of the discount factor

---

19This issue is related to the literature on the importance of initial endowments on subsequent outcomes of a dynamic process (Heckman (1981, 1991)). As suggested by Heckman it is important distinguish between heterogeneity (how persistent is the effect of initial endowments on outcomes), and state dependence (whether subsequent experiences attenuate or accentuate the effect of initial endowments). It is possible that a raw correlation between wealth on consumption growth reflects a causal influence of wealth on consumption growth (state dependence), or the fact that individuals differ in time preferences and more patient people accumulate more wealth accumulate (heterogeneity).
decreasing in wealth. Another way to control for the endogeneity problem is to give different levels of consumption to the subjects before an experiment to see which subjects are more patient. Implementing this idea with human subjects is difficult, so rats were used instead. The results were in favor of the view that the discount factor is decreasing in wealth as reported in Kagel, Battalio, Green (1995, Chapter 7, Section 3).

Using the Panel Study of Income Dynamics (PSID), Lawrance (1991) employed the Euler equation approach to estimate the endogenous discount factor model. In principle, her instrumental variable method should take care of the endogeneity problem. Lawrance found evidence in favor of the discount factor increasing in wealth. However, Ogaki and Atkeson (1997) point out that Lawrance did not allow the intertemporal elasticity of substitution (IES) to vary with wealth. Ogaki and Atkeson allow both the IES and the discount factor to vary with wealth for a panel data of households in Indian villages. They find evidence in favor of the view that the discount factor is constant and that the IES is increasing in wealth. It is possible that the discount factor is decreasing in wealth for richer households, but Lawrance found the opposite result because she did not allow the IES to change. Ogawa (1993) argues that his empirical results from Japanese aggregate data are consistent with a combination of Fisher’s and Uzawa’s hypotheses.

Overall, we think that the empirical evidence is consistent with the view that reality is best described by a combination of the two hypotheses. In our view, a child who experiences low consumption will grow to be more patient because she can more vividly imagine future misery. At the same time, a wealthier parent is more likely to invest in the child’s human capital to help the child see the future more vividly. In this paper, we aim to develop a simple model that captures our intuition of tough love, which is that a parent allows suffering so that the child can learn to be more patient. Such a model will imply that transfers decrease when the child exogenously becomes

20They control the endogeneity problem by analyzing how the discount factor changes with the size of a prize obtained in another experiment.
impatient. For this purpose, we will assume that low consumption during childhood leads to more patience when the child grows up while abstracting from the human capital nature of endogenous discounting.

Finally, in our model, parents with higher discount factors have stronger tough love motives, other things being equal. Horioka et al (2009) provide empirical evidence related to this implication of the model. They used a unique U.S. and Japanese survey data collected by the Osaka University that contained hypothetical survey questions concerning parents’ tough love behavior and their attitude toward intertemporal choices of receiving cash at different time points (to measure parental discount factors). Their empirical results suggest that parents with lower time discount rates (higher discount factors) for their own financial decisions are more likely to behave toward their children with tough love.

2.3 A Consumption Good Economy

The main purpose of this section is to develop and analyze a model of altruism in which the parent’s transfers decrease when the child exogenously becomes impatient. For this purpose, we modify the standard altruism model in two ways: the child’s discount factor is endogenous in that higher consumption in her childhood causes her discount factor to be lower, and the parent evaluates the child’s lifetime utility with a high constant discount factor. The modified model is called the tough love altruism model. In order to gain a clear understanding of the properties of the model, we consider the simplest setting for our purpose. We will compare the tough love model with the standard altruism model and with two other altruism models that modify the standard altruism model with only one of our tough love model’s features.

Imagine a three-period model economy with two agents, the parent and the child. For simplicity we consider the case of a single parent and a single child. The three periods considered are
childhood, work and retirement. The model has six features. First, the parent not only cares about his own consumption, but is also altruistic toward the child. He assigns a weight of \( \eta \) to his own utility where \( 0 < \eta < 1 \). The child on the other hand is a non-altruist and derives utility only from her own consumption stream \( \{C_t\}_{t=1}^3 \). Second, the life of the parent and the child overlap only in period 1. Third, transfers, \( T \), are made only in period 1.\(^{21} \) Fourth, income of both the parent and the child is given exogenously. Fifth, the child is borrowing constrained in period 1. Lastly, there is no uncertainty in the economy.

**Standard Altruism Model**

We start our analysis with the standard altruism model. In this model, both the parent and the child use the same constant discount factor when evaluating the child’s future utility. The parent’s problem is,

\[
\max_T \left[ \eta \, v(y_1 - T) + (1 - \eta) \left[ u(C_1^*) + \beta_2 u(C_2^*) + \beta_2 \beta_3 u(R^2(y_1 + T + \frac{y_2}{R} - C_1^* - \frac{C_2^*}{R})) \right] \right],
\]

subject to

\[
C_1 = y_1 + T
\]

(2.1)

and

\[
\{C_1^*, C_2^*\} \equiv \arg \max_{C_1, C_2} \left[ u(C_1) + \beta_2 u(C_2) + \beta_2 \beta_3 u(R^2(y_1 + T + \frac{y_2}{R} - C_1 - \frac{C_2}{R})) \right].
\]

(2.3)

\(^{21}\) We assume that transfers are made from the parent to the child and there are no reverse transfers.
The following notation will be used: \( u(C) \) and \( v(C) \) are the standard concave utility functions of the parent and the child respectively. \( \beta_{t,p} \) is the discount factor used by the parent to evaluate the child’s future utility and \( \beta_{t,k} \) is the discount factor used by the child in period \( t \).\(^{22}\) We denote the parent’s income in period 1 by \( y_p \). \( y_1 \) and \( y_2 \) represent the child’s period 1 and period 2 income levels.\(^{23}\) \( R \) is the gross nominal interest rate.

We are interested in the case where the borrowing constraint is binding for the child and assume that the parameters are such that the constraint is binding. We substitute out the borrowing constraint faced by the child in period 1 and rewrite the parent’s optimization problem as

\[
\max_T \left[ \eta v(y_p - T) + (1 - \eta) \left[ u(y_1 + T) + \beta_2 u(C_2^*) + \beta_2 \beta_3 u(R(y_2 - C_2^*)) \right] \right], \quad (2.4)
\]

subject to

\[
\{C_2^*\} \equiv \arg \max_{C_2} \left[ u(C_2) + \beta_3 u(R(y_2 - C_2)) \right]. \quad (2.5)
\]

Let us focus on the child’s optimization program. From the first order condition for the child’s problem described in equation (2.5), we get:

\[
u_{C_2}(C_2) - \beta_3 R u_{C_2}(R(y_2 - C_2)) = 0 \quad (2.6)\]

where,

\[
u_x(x) = \frac{\partial u(x)}{\partial x}.
\]

Assuming that the utility function satisfies conditions for the Implicit Function Theorem,\(^{24}\) we can solve equation (2.6) for \( C_2 \) as a function of the model parameters and the state variables:

\[
C_2^* = C_2(y_2; \beta_3, R). \quad (2.7)
\]

\(^{22}\)In this model we have \( \beta_{t,p} = \beta_{t,k} = \beta_t \).

\(^{23}\)For simplicity we assume the child gets no income in the last period of her life and simply consumes her savings from past periods.

\(^{24}\)\( u(.) \) is continuously differentiable with a non-zero Jacobian.
The optimal period 2 consumption for the child is independent of the period 1 transfers of the parent and hence can be dropped from the parent’s optimization program. Hence we can rewrite the parent’s problem described by equations (2.4) and (2.5) as:

\[
\max_T \left[ \eta v(y_p - T) + (1 - \eta)u(y_1 + T) \right]. \tag{2.8}
\]

The first order condition for the above problem is given by,

\[
-\eta v_T(y_p - T) + (1 - \eta)u_T(y_1 + T) = 0. \tag{2.9}
\]

Again, using the implicit function theorem, we get,

\[
T^* = T(y_p, y_1, \eta). \tag{2.10}
\]

We consider comparative statics for exogenous changes in the discount factor of the child for the standard altruism model. Specifically, we decrease the child’s discount factor \( \beta_3 \) and observe how this rise in the child’s impatience is accommodated by the parent in terms of a change in period 1 transfers. From equation (2.10), optimal period 1 transfers by the parent in the standard altruism model are in fact independent of the child’s discount factor implying that an exogenous change in the child’s discount factor will have no effect on the period 1 transfers made by the parent. Hence, parents with the standard altruism motive will not respond to increasingly impatient behavior of the child. As discussed earlier, this implication of the model does not seem consistent with data where we find that both pecuniary and non-pecuniary punishments are used by parents to influence their children’s behavior and outcomes.
**Tough Love Altruism Model**

We propose a Tough Love Altruism model that provides for a channel through which parents can influence the child’s economic behavior. We introduce the tough love motive of the parent via asymmetric time preferences between generations and endogenous discounting. This model predicts that the transfer to the child in period 1 will decrease when the child’s discount factor exogenously decreases, for a wide range of parameters. In this model, the parent uses a constant and high discount factor to evaluate the child’s lifetime utility while the child herself uses a discount factor which is endogenously determined as a decreasing function of her period 1 consumption:

\[
\beta_{t,k}(C_1); \quad \frac{\partial \beta_{t,k}}{\partial C_1} < 0.
\]

With the borrowing constraint faced by the child in period 1, her discount factor is given by \(\beta_{t,k}(y_1 + T)\).

Now, the parent solves the following optimization problem,

\[
\max_T \left[ \eta v(y_p - T) + (1 - \eta) \left[ u(y_1 + T) + \beta_{2,p} u(C_2^*) + \beta_{3,p} \beta_{3,p} u(R(y_2 - C_2^*)) \right] \right], \quad (2.11)
\]

subject to

\[
\{ C_2^* \} \equiv \arg \max_{C_2} \left[ u(C_2) + \beta_{3,k}(y_1 + T) u(R(y_2 - C_2)) \right]. \quad (2.12)
\]

From the first order condition for the child’s problem described in equation (2.12), we get

\[
u_{C_2}(C_2) - \beta_{3,k}(y_1 + T) Ru_{C_2}(R(y_2 - C_2)) = 0. \quad (2.13)
\]
Using the implicit function theorem, we write the solution of (2.13) for \( C_2 \) as a function of the model parameters and the state variables.

\[
C^*_2 = C_2(y_2, \beta_{3,k}(y_1 + T), R).
\]  

It can be easily shown that at the optimum

\[
\frac{\partial C^*_2}{\partial \beta_k} < 0 ; \quad \frac{\partial C^*_2}{\partial T} > 0
\]

**Relationship between Transfers and the Child’s Discount Factor**

The parent accounts for \( C^*_2 \) when maximizing his utility by choosing transfers (T). From the first order condition for the parent’s problem described in equation (2.11) and (2.12), we get

\[
-\eta u'(y_p - T) + (1 - \eta) \left( u'(y_1 + T) + \beta_p u'(C^*_2) \frac{\partial C^*_2}{\partial T} - \beta^2_p R u'(R(y_2 - C^*_2)) \frac{\partial C^*_2}{\partial T} \right) = 0
\]

Let \( T^* \) denote optimal parental transfers which must satisfy equation (2.15) above. So we can rewrite the above equation as

\[
v'(y_p - T^*) = \frac{1 - \eta}{\eta} \left( u'(y_1 + T^*) + \beta_p u'(C^*_2) \frac{\partial C^*_2}{\partial T} - \beta^2_p R u'(R(y_2 - C^*_2)) \frac{\partial C^*_2}{\partial T} \right)
\]

Now consider an exogenous change in the child’s discount factor \( (\beta_k) \). Then from equation (2.16) above we can derive the change in \( T^* \):

\[
-\eta u''(y_p - T^*) \frac{\partial T^*}{\partial \beta_k} = \left( \frac{1 - \eta}{\eta} \right) u''(y_1 + T^*) \frac{\partial T^*}{\partial \beta_k} + \left( \frac{1 - \eta}{\eta} \right) \frac{\partial}{\partial \beta_k} \left[ \beta_p u'(C^*_2) \frac{\partial C^*_2}{\partial T} - \beta^2_p R u'(R(y_2 - C^*_2)) \frac{\partial C^*_2}{\partial T} \right]
\]

Rearranging terms we get,

\[
\frac{\partial T^*}{\partial \beta_k} = A \ast \left( \frac{\partial}{\partial \beta_k} \left[ \beta_p u'(C^*_2) \frac{\partial C^*_2}{\partial T} - \beta^2_p R u'(R(y_2 - C^*_2)) \frac{\partial C^*_2}{\partial T} \right] \right)
\]
where

\[ A = -\left(\frac{1-\eta}{\eta}\right) \]

\[ v''(y_p - T^*) + \left(\frac{1-\eta}{\eta}\right) u''(y_1 + T^*) \]

Given concavity of \(v(.)\) and \(u(.)\) we know that \(A > 0\). Hence,

\[
\text{sign} \left( \frac{\partial T^*}{\partial \beta_k} \right) = \text{sign} \left( \frac{\partial}{\partial \beta_k} \left[ \beta_p u'(C_2^*) \frac{\partial C_2^*}{\partial T} - \beta_p^2 R u'(R(y_2 - C_2^*)) \frac{\partial C_2^*}{\partial T} \right] \right) \tag{2.18}
\]

Then \(\frac{\partial T^*}{\partial \beta_k} > 0\) if and only if,

\[
\frac{\partial}{\partial \beta_k} \left[ \beta_p u'(C_2^*) \frac{\partial C_2^*}{\partial T} - \beta_p^2 R u'(R(y_2 - C_2^*)) \frac{\partial C_2^*}{\partial T} \right] > 0
\]

The term in the square bracket in the equation above represents parental evaluation of the benefit (cost) associated with a change in transfers on the child’s period 2 and period 3 utilities. If this term is increasing in the child’s discount factor, parents will always decrease transfers with a fall in the child’s discount factor. We call this the tough love motive of the parent. This result shows that whether or not the parent increases or decreases the transfer in response to an exogenous change in the child’s patience depends on the term related to child’s period 2 and period 3 utilities. In order to develop intuition on this term, we now turn to simulations.

**Simulated Response of Parents to an Exogenous Fall in the Child’s Discount Factor**

Unlike the standard altruism model, the optimal period 2 consumption for the child in the Tough Love Altruism model is not independent of the first period transfers from the parent and hence cannot be dropped from the parent’s optimization program. As a result, we cannot use the same methodology for solving the parent’s problem as in the standard altruism model. In the Tough Love Altruism model, there is no closed form solution to the parent’s problem for any functional form of the utility function. Hence, we solve the problem described in equations (2.11) and (2.12)
numerically as a non linear root finding problem. For this purpose we impose the following parameterization:\textsuperscript{25}

\begin{equation}
    u(C) = v(C) = \frac{C^{1-\sigma}}{1-\sigma}.
\end{equation}

The discount factor is given by,

\begin{equation}
    \beta(y_1 + T) = \beta_0 + \frac{1}{1 + a(y_1 + T)} \quad \text{where} \quad a > 0 \text{ and } \beta_0 \leq 0.
\end{equation}

Hence, as the parameter $\beta_0$ decreases, at any given level of $y_1$ and $T$, the discount factor falls, implying more impatient behavior on the part of the child.

We consider comparative statics for exogenous changes in the discount factor of the child in the Tough Love Altruism model. For this purpose, I first solve the model for the parametric specification given in (2.19) and (2.20) and a given set of model parameter values. This gives us the benchmark optimal transfers and consumption stream, $\{T^*, C_1^*, C_2^*, C_3^*\}$.

Consider an exogenous decrease in the child’s discount factor. Formally, this is achieved by decreasing the preference parameter, $\beta_0$. The results for a given set of model parameter values are summarized in Table 2.1. As we observe from Table 2.1, period 1 transfers fall monotonically from 0.9989 to 0.7075 as we decrease the parameter, $\beta_0$, from 0.0 to $-0.8$. Thus, the main finding of the simulation exercise is that there is a monotonic decline in period 1 transfers by parents to the child with a rise in the child’s impatience as captured by the falling value of the parameter, $\beta_0$. This is in sharp contrast to the comparative statics result for the standard altruism model in which $\textsuperscript{25}$

Our simulation results are robust to alternative parametric specifications of the utility function and the discount factor function.
the optimal period 1 transfers are independent of the child’s discount factor.\footnote{For brevity, I have only presented simulation results for one parametric specification. In Appendix A, I present these results for several alternative parametric specifications (see Tables A1 through A7). The simulation results presented here remain qualitatively unchanged with parental transfers monotonically decreasing with a fall in child’s discount factor.}

\begin{table}[h]
\centering
\begin{tabular}{lcccc}
\hline
\textbf{Global Parameters} & & & & \\
\hline
& $\eta = 0.5; \sigma = 1.5; R = 1.2;$ & & & \\
& $\beta_p = 1; y_1 = y_2 = 3; y_p = 5; a = 0.01$ & & & \\
\hline
\textbf{Optimum} & $\beta_0 = 0$ & $\beta_0 = -0.4$ & $\beta_0 = -0.6$ & $\beta_0 = -0.8$ \\
$T^*$ & 0.9989 & 0.9736 & 0.9273 & 0.7075 \\
$C_1^*$ & 3.9989 & 3.9736 & 3.9273 & 3.7075 \\
$C_2^*$ & 1.5651 & 1.8285 & 2.0295 & 2.3397 \\
$C_3^*$ & 1.7218 & 1.4058 & 1.1646 & 0.7924 \\
$\beta(C_1^*)$ & 0.9615 & 0.5618 & 0.3622 & 0.1643 \\
\hline
\end{tabular}
\caption{Tough Love Altruism Model ($\sigma > 1$)}
\end{table}

In intergenerational altruism models, an important parameter determining the optimal solution is $\sigma$ which measures the elasticity of intertemporal substitution. Table 2.2 presents the simulations with $\sigma < 1$. Again, we find that transfers decline monotonically as we lower the child’s discount factor by decreasing $\beta_0$.

The intuition behind this positive relationship between transfers and child’s discount factor in the Tough Love Altruism model is as follows. Consider a child who evaluates her consumption stream for the three periods of childhood (period 1), work (period 2) and retirement (period 3). In the Tough Love Altruism model, the parent with the tough love motive attempts to align the growth rate of the child’s consumption from period 2 to period 3 with the parent’s high discount factor.

Global Parameters
\( \eta = 0.5; \sigma = 0.7; R = 1.2; \)
\( \beta_p = 1; y_1 = y_2 = 3; y_p = 5; a = 0.01 \)

<table>
<thead>
<tr>
<th>Optimum</th>
<th>( \beta_0 = 0 )</th>
<th>( \beta_0 = -0.4 )</th>
<th>( \beta_0 = -0.6 )</th>
<th>( \beta_0 = -0.8 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( T^* )</td>
<td>0.9976</td>
<td>0.9449</td>
<td>0.8729</td>
<td>0.6829</td>
</tr>
<tr>
<td>( C^*_1 )</td>
<td>3.9976</td>
<td>3.9449</td>
<td>3.8729</td>
<td>3.6829</td>
</tr>
<tr>
<td>( C^*_2 )</td>
<td>1.4834</td>
<td>2.0342</td>
<td>2.3924</td>
<td>2.7725</td>
</tr>
<tr>
<td>( C^*_3 )</td>
<td>1.8199</td>
<td>1.1589</td>
<td>0.7291</td>
<td>0.2730</td>
</tr>
<tr>
<td>( \beta(C^*_1) )</td>
<td>0.9616</td>
<td>0.5620</td>
<td>0.3627</td>
<td>0.1645</td>
</tr>
</tbody>
</table>

Table 2.2: Tough Love Altruism Model (\( \sigma < 1 \))

If the parent uses a higher discount factor to evaluate the child’s lifetime utility than the child’s discount factor, the slope of consumption of the child from period 2 to period 3 is too small (either consumption grows too slowly or drops too fast) compared with what the parent likes. In this case, the parent has a tough love motive to decrease the transfer so that the child will learn to be more patient and increase the slope. When the child becomes impatient because of an exogenous factor, the slope drops, the tough love motive intensifies, and the transfer decreases.

2.4 How Important is Tough Love?

The main result of our tough love altruism model is that the parent will decrease transfers in response to an exogenous decrease in the child’s discount factor. The tough love model modifies the standard altruism model in two ways. Do we need both of these modifications in order to obtain this result? In order to answer this question, we analyze two alternative models of altruism. First, we modify the standard altruism model by assuming that the parent evaluates the child’s lifetime utility by a higher discount factor than the child’s. We however, do not introduce endogenous discounting in this model. This model is called the paternalistic altruism model. Second, we modify
the standard altruism model by introducing endogenous discounting on the part of the child. However, we assume that the parent will use the child’s endogenous discounting to evaluate the child’s lifetime utility.

**Paternalistic Altruism Model**

In this model both the parent and the child use constant discount factors to evaluate future utility. However, unlike the standard altruism model, here the discount factor used by the parent is higher than the child’s discount factor, i.e. $\beta_{t,p} > \beta_{t,k}$ where $\beta_{t,p}$ is the discount factor used by the parent to evaluate the child’s future utility and $\beta_{t,k}$ is the discount factor used by the child in period $t$. The parent’s problem is:

$$
\max_T \left[ \eta v(y_p - T) + (1 - \eta) \left[ u(y_1 + T) + \beta_{2,p} u(C^*_2) + \beta_{2,p} \beta_{3,p} u(R(y_2 - C^*_2)) \right] \right],
$$

subject to

$$
\{C^*_2\} \equiv \arg \max_{C_2} \left[ u(C_2) + \beta_{3,k} u(R(y_2 - C_2)) \right].
$$

As before, we solve the child’s optimization problem first, which gives us the optimal period 2 consumption of the child:

$$
C^*_2 = C_2(y_2, \beta_{3,k}, R).
$$

The optimal period 2 consumption for the child is independent of the period 1 transfers of the parent, so it can be dropped from the parent’s optimization program. We rewrite the parent’s problem described by equations (2.21) and (2.22) as
\[
\max_T \left[ \eta v(y_p - T) + (1 - \eta)u(y_1 + T) \right]. \tag{2.24}
\]

The first order condition for the above problem is given by:

\[
-\eta v_T(y_p - T) + (1 - \eta)u_T(y_1 + T) = 0. \tag{2.25}
\]

The above equation in principle can be solved for optimal period 1 transfers,

\[
T^* = T(y_p, y_1, \eta). \tag{2.26}
\]

We now consider an exogenous decrease in the child’s discount factor, \(\beta_{3,k}\). From equation (2.26) optimal period 1 transfers by the parent are independent of the discount factor of the child. Therefore, like the standard altruism model, in this model there is no effect of a decrease in the discount factor on the period 1 transfers. Note that this is a special case of the tough love altruism model and the result of Section III trivially applies here. In this model

\[
\frac{\partial C^*_2}{\partial T} = 0,
\]

which implies,

\[
\left[ \beta_p u'(C^*_2) \frac{\partial C^*_2}{\partial T} - \beta^2_p Ru'(R(y_2 - C^*_2)) \right] = 0,
\]

and hence we get

\[
\frac{\partial T^*}{\partial \beta_k} = 0.
\]
Endogenous Altruism Model

In this model, as was assumed in the tough love altruism model, the discount factor used by the child is endogenously determined as a decreasing function of her period 1 consumption.

\[ \beta_{t,k}(c_1) \ ; \quad \frac{\partial \beta_{t,k}}{\partial c_1} < 0. \]

With the borrowing constraint faced by the child in period 1, the discount factor is given by \( \beta_{t,k}(y_1 + T) \). However, unlike the tough love altruism model, the parent also uses the above discount factor for evaluating the child’s future utility. So the key difference is the assumption:

\[ \beta_{t,p}(x) = \beta_{t,k}(x). \]

The parent’s problem in this model is:

\[
\max_{C_2} \left[ \eta v(y_p - T) + (1 - \eta) \left[ u(y_1 + T) + \beta_{2,p}(y_1 + T)u(C_2^*) + \beta_{2,p}(y_1 + T)\beta_{3,p}(y_1 + T)u(R(y_2 - C_2^*)) \right] \right],
\]

subject to

\[
\{C_2^*\} \equiv \arg \max_{C_2} \left[ u(C_2) + \beta_{3,k}(y_1 + T)u(R(y_2 - C_2)) \right]. \tag{2.28}
\]

From the first order condition for the child’s problem we get:

\[
u_{C_2}(C_2) - \beta_{3,k}(y_1 + T)Ru_{C_2}(R(y_2 - C_2)) = 0. \tag{2.29}
\]

The above equation yields the optimal period 2 consumption of the child

\[ C_2^* = C_2(y_2, \beta_{3,k}(y_1 + T), R). \tag{2.30}\]

The optimal period 2 consumption for the child is not independent of period 1 transfers of the parent and hence cannot be dropped from the parent’s optimization program. We solve the problem
described in equations (2.27) and (2.28) numerically as a non-linear root finding problem. The 
solution method and the parametrization adopted is identical to the one we used for the tough love 
altruism model.

We now consider an exogenous decrease in the discount factor of the child. For comparative 
statics, we make the child more impatient by decreasing the preference parameter $\beta_0$, and then 
trace out the effect of this change on the period 1 transfers, $T$. The results for the assumed set 
of model parameter values are summarized in Table 2.3. Again, we find that as $\beta_0$ is reduced 
monotonically, parents in the endogenous altruism model will decrease transfers.

<table>
<thead>
<tr>
<th>Global Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\eta = 0.5; \sigma = 1.5; R = 1.2; $</td>
</tr>
<tr>
<td>$y_1 = y_2 = 3; y_p = 5 ; a = 0.01$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Optimum</th>
<th>$\beta_0 = 0$</th>
<th>$\beta_0 = -0.4$</th>
<th>$\beta_0 = -0.6$</th>
<th>$\beta_0 = -0.8$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T^*$</td>
<td>1.4343</td>
<td>1.3265</td>
<td>1.2667</td>
<td>1.1988</td>
</tr>
<tr>
<td>$C_1^*$</td>
<td>4.4343</td>
<td>4.3265</td>
<td>4.2667</td>
<td>4.1988</td>
</tr>
<tr>
<td>$C_2^*$</td>
<td>1.5672</td>
<td>1.8313</td>
<td>2.0333</td>
<td>2.3493</td>
</tr>
<tr>
<td>$C_3^*$</td>
<td>1.7193</td>
<td>1.4025</td>
<td>1.1600</td>
<td>0.7809</td>
</tr>
<tr>
<td>$\beta(C_1^*)$</td>
<td>0.9575</td>
<td>0.5585</td>
<td>0.3591</td>
<td>0.1597</td>
</tr>
</tbody>
</table>

Table 2.3: Endogenous Altruism Model ($\sigma > 1$)

The results summarized in Table 2.3 above seem to suggest that endogenous discounting is 
enough to obtain the result that transfers decrease in response to an exogenous fall in the child’s 
discount factor. However, unlike the results of the tough love model, this result is very sensitive to 
the assumption made on $\sigma$. Table 2.4 presents simulation results with $\sigma < 1$. Now we find that as 
$\beta_0$ falls, transfers increase monotonically. Hence, with the endogenous altruism model, depending 
on the model parameters, we may get a counterintuitive result where parents reward the impatience
of the child. Thus, in order to obtain the result that the parent’s transfer decreases in response to an exogenous decrease in the child’s discount factor over a wide range of parameters, we need to introduce both endogenous discounting and paternalistic evaluation by the parent of the child’s lifetime utility. The intuition behind this result is as follows. In this model, the parent cares about changes in the level of the child’s life time utility caused by changes in the transfer. Thus, the transfer may increase when there is an exogenous decline in the child’s discount factor. This is in contrast with the tough love model, in which the parent only cares about changes in the slope of consumption in the second and third periods caused by changes in the transfer.

### 2.5 Are Parents Loving in the Tough Love Altruism Model?

The main implication of our tough love altruism model is that the parent, driven by concern for the child’s long run welfare, would reduce transfers in response to impatient behavior on the part of the child. Given that, in our model, the child is assumed to be borrowing constrained in the first period of her life, this implies a lower first period consumption and hence a lower first period

<table>
<thead>
<tr>
<th>Optimum</th>
<th>$\beta_0 = 0$</th>
<th>$\beta_0 = -0.4$</th>
<th>$\beta_0 = -0.6$</th>
<th>$\beta_0 = -0.8$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T^*$</td>
<td>0.2111</td>
<td>0.4393</td>
<td>0.5438</td>
<td>0.6323</td>
</tr>
<tr>
<td>$C_1^*$</td>
<td>3.2111</td>
<td>3.4393</td>
<td>3.5438</td>
<td>3.6323</td>
</tr>
<tr>
<td>$C_2^*$</td>
<td>1.4753</td>
<td>2.0264</td>
<td>2.3866</td>
<td>2.7716</td>
</tr>
<tr>
<td>$C_3^*$</td>
<td>1.8297</td>
<td>1.1683</td>
<td>0.7361</td>
<td>0.2740</td>
</tr>
<tr>
<td>$\beta(C_1^*)$</td>
<td>0.9689</td>
<td>0.5668</td>
<td>0.3658</td>
<td>0.1650</td>
</tr>
</tbody>
</table>

Table 2.4: Endogenous Altruism Model ($\sigma < 1$)
utility for the child. In this section, we ask a question: is the parent in our model loving or is he simply driven by a paternalistic tendency of controlling the child’s consumption?

For this purpose, we compare our tough love altruism model and the endogenous altruism model (discussed in section 2.4). The only difference between these two models is that in the former, the parent uses his own high constant discount factor to evaluate the child’s lifetime utility while in the latter, the parent honors the endogenous discount factor of the child while evaluating her lifetime utility. Since the child optimizes by choosing a consumption stream given her parent’s transfers, with full knowledge of her endogenous discounting, during childhood she prefers the parent in the endogenous discounting altruism model to the parent in the tough love model. This is because without a tough love motive transfers in the endogenous altruism model will be higher than those received from the tough love parent. However, it may be possible that the child will appreciate parental tough love after she grows up in retrospect, in which case the parent in our model can be viewed as loving rather than just paternalistic.

In order to investigate this possibility of the child’s retrospective appreciation for parental tough love, we conduct the following thought experiment. Consider a child who had a parent with the tough love motive and hence attains a discount factor in line with her parent’s desire to make her patient. Imagine that, after she grows up, she uses this discount factor to evaluate the resulting consumption stream for the three periods of childhood, work and retirement. Now, imagine that she compares her tough love parent with a hypothetical parent who honors her endogenous discounting in evaluating her lifetime utility. For this purpose, she evaluates her lifetime utility using the same discount factor but with a counterfactual consumption stream that she would have obtained from the endogenous discounting altruism parent. As long as the borrowing constraint is binding, the child has a higher lifetime utility for the last two periods with her consumption stream from the tough love altruism model than the counterfactual consumption stream from the endogenous
altruism model. Otherwise, she would not be optimizing. However, she will have a lower utility level in her childhood under the tough love altruism regime. In this experiment we investigate if this lower utility level in the childhood is compensated enough by a higher utility level from the last two periods of her life.

For this experiment, we extend our model in an important dimension. Until now, for notational simplicity, we assumed that the three periods of the child’s life are of equal duration. In reality, we can expect them to vary. Allowing the duration to vary, we denote that of the childhood period by $\tau_1$, that of the work period by $\tau_2$, and that of the retirement period by $\tau_3$. 27 We imagine the childhood period of the model to correspond with the period around high school and the early years of college in which children may engage in part time work (e.g. 16-20 years of age) and set the duration to be 5 years. 28 The benchmark duration of the work period of the model is set to be 40 years, and corresponds to age between 21-60 years. The benchmark duration for the retirement period is set to be 20 years, and corresponds to ages between 61-80 years.

After allowing for these varying durations, the parent’s problem in the tough love altruism model is summarized by equations (2.31) and (2.32).

$$\max_T \left[ \tau_1 \eta v(y_p - T) + (1 - \eta) \left[ \tau_1 u(y_1 + T) + \tau_2 \beta_{2,p} u(C_2^*) + \tau_3 \beta_{3,p} u(R(y_2 - C_2^*)) \right] \right],$$ (2.31)

subject to

$$\{C_2^*\} \equiv \arg \max_{C_2} \left[ \tau_2 u(C_2) + \tau_3 \beta_{3,k}(y_1 + T) u(R(y_2 - C_2)) \right].$$ (2.32)

27 For the benchmark case for this section and the next section in which the leisure-work choice is introduced, we abstract from the child’s early life in which she does not face the work-leisure choice.

28 Cunha, Heckman, Lochner and Masterov (2006) present a survey of empirical evidence that later interventions in adolescent years can affect non-cognitive skills like patience, self control, temperament, time preferences, etc. while these interventions cannot affect cognitive skills.
Similarly, the parent in the endogenous altruism model maximizes:

$$
\max_T \left[ \tau_1 \eta v(y_p - T) + (1 - \eta) \left[ \tau_1 u(y_1 + T) + \tau_2 \beta_2(y_1 + T) u(C_2^*) \right. \right.
$$

$$
\left. + \tau_3 \beta_2(y_1 + T) \beta_3(y_1 + T) u(R(y_2 - C_2^*)) \left] \right] ,
$$

subject to

$$
\{C_2^*\} \equiv \arg \max_{C_2} \left[ \tau_2 u(C_2) + \tau_3 \beta_3(y_1 + T) u(R(y_2 - C_2^*)) \right] .
$$

To compare the child’s lifetime utility in both models, we solve them for a given value of model parameters. However, to make this comparison, we evaluate the child’s lifetime utility in both the models using the discount factor obtained under the tough love model, namely $\beta(C_{1,TL}^*)$. Let $C_{TL}^* = \{C_{1,TL}^*, C_{2,TL}^*, C_{3,TL}^*\}$ and $C_{END}^* = \{C_{1,END}^*, C_{2,END}^*, C_{3,END}^*\}$ denote the child’s optimal lifetime consumption stream in the tough love altruism and endogenous altruism models respectively for a given value of the preference parameter $\beta_0$. Then, equations (2.35) and (2.36) below are expressions for the child’s lifetime utility in the tough love altruism and the endogenous altruism model respectively.

$$
V(C_{TL}^*) = \tau_1 u(C_{1,TL}^*) + \beta_2(C_{1,TL}^*) \tau_2 u(C_{2,TL}^*) + \beta_2(C_{1,TL}^*) \beta_3(C_{1,TL}^*) \tau_3 u(C_{3,TL}^*),
$$

$$
V(C_{END}^*|\beta_2(C_{1,TL}^*), \beta_3(C_{1,TL}^*)) = \tau_1 u(C_{1,END}^*) + \beta_2(C_{1,TL}^*) \tau_2 u(C_{2,END}^*)
$$

$$
+ \beta_2(C_{1,TL}^*) \beta_2(C_{1,TL}^*) \tau_3 u(C_{3,END}^*).
$$

\(^{29}\)We compound the gross interest rate and the inter period discount factor to account for varying duration of the time periods.
We compute the child’s utility level in the two models for a particular set of model parameter values using the above two expressions. The results of this exercise are provided in Table 2.5. With the parameter values described in the table, we find that the child’s lifetime utility in the endogenous altruism model evaluated at $\beta(C^*_1, TL)$ is lower than the utility level attained in the tough love altruism model. Thus these results depict that there exist reasonable parameter values under which the child appreciates parental tough love in retrospect. In reality, some children with tough parents appreciate what their parents have done after growing up and others do not. With different parameter values, our model can explain both types of children.\(^{30}\)

<table>
<thead>
<tr>
<th>Global Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\eta = 0.5$, $\sigma = 1.5$; $r = 1.02$; $a = 0.01$; $\beta_p = 1$</td>
</tr>
<tr>
<td>$y_1 = 1$; $y_2 = 10$; $y_p = 10$; $\tau_1 = 5$; $\tau_2 = 40$; $\tau_3 = 20$</td>
</tr>
</tbody>
</table>

| Model                  | $C_1^*$ | $C_2^*$ | $C_3^*$ | $\beta(C^*_1)$ | $V(C^*)$ | $V(C^*_{END}|\beta(C^*_1,TL))$ |
|------------------------|---------|---------|---------|-----------------|---------|---------------------------------|
| Tough Love Altruism    | 3.5341  | 7.0943  | 5.2632  | 0.9659          | -25.2188| -                               |
| Endogenous Altruism    | 10.0241 | 8.9174  | 1.9610  | 0.9089          | -7.9071 | -25.5188                        |

Table 2.5: Child’s lifetime Utility Comparison

2.6 Tough Love Altruism Model with Leisure

Until now we have considered an economy where agents derive utility only from consumption. In this section we generalize our setup in an important dimension by allowing for leisure as a choice.\(^{30}\) For example, if we set $\tau_1 = \tau_2 = \tau_3$, with the remaining parameter values specified in Table 2.5, the child’s lifetime utility is higher for the consumption stream of the endogenous altruism model evaluated at $\beta(C^*_1,TL)$.\(^{30}\)
variable for the child. The purpose is to see how transfers and income are related in the tough love altruism model when leisure is endogenous. This is motivated by empirical evidence against the standard altruism model’s redistributive neutrality property (also called the transfer derivative restriction). The standard altruism model implies that an exogenous dollar decrease in the child’s income coupled with a dollar increase in the parent’s income will lead to a dollar increase in transfers from the parent to the child. There is empirical evidence against this redistributive neutrality. Cox (1987) studied the relationship between transfers received and income of the recipient. Using President’s Commission on Pension Policy (PCPP) data he found evidence that transfers are not correlated with the recipient’s income as implied by the redistributive neutrality property of a static version of the standard altruism model. Altonji, Hayashi and Kotlikoff 1997) strengthened evidence against the redistributive neutrality implied by a dynamic version of the model. They used PSID data and found that transfers only increase by 13 cents even when the recipient child is borrowing constrained.

The tough love model also implies redistributive neutrality.31 Because the parent optimizes the child’s consumption level in the first period, if an exogenous factor changes the distribution of income for the parent and the child, the parent neutralizes the change by changing transfers.32 However, this redistributive neutrality only holds for exogenous income changes. We study below how endogenous changes in income caused by an exogenous change in the child’s discount factor is related to transfers.

We continue to assume perfect information. In our set up, this implies that the parent can fully observe the child’s effort level. The remaining model assumptions are retained with transfers being made only in period 1 and the child being borrowing constrained in period 1. The following

31 For a general proof for redistributive neutrality under Tough Love Altruism Model please see Appendix A.

32 The paternalistic and endogenous discount altruism models also imply redistributive neutrality. The proofs for redistributive neutrality of the models in this paper are available by the authors on request.
notation is used. \( L_1 \) and \( L_2 \) denote the amount of leisure consumed by the child in period 1 and period 2 respectively. \( w_1 \) and \( w_2 \) denote the wage income of the child in the two periods. For simplicity we assume that the child earns no wage income in period 3 and simply consumes her past savings. The parent’s problem is:

\[
\max_T \eta v(y_p - T) + (1 - \eta) \left[ \tau_1 u(w_1(1 - L_1^*) + T, L_1^*) + \beta_2 \tau_2 u(C_2^*, L_2^*) + \beta_3 \tau_3 u(R(w_2(1 - L_2^*) - C_2^*)) \right],
\]

subject to

\[
\{C_2^*, L_1^*, L_2^*\} \equiv \arg \max_{C_2, L_1, L_2} \left[ \tau_1 u(w_1(1 - L_1) + T, L_1) + \beta_2 \tau_2 u(C_2, L_2) + \beta_3 \tau_3 u(R(w_2(1 - L_2) - C_2)) \right].
\]

From the first order conditions for the child’s problem we get:

\[
\tau_2 u_{C_2}(C_2, L_2) - \beta_{3,k}(w_1(1 - L_1) + T) R \tau_3 u_{C_2}(R(w_2(1 - L_2) - C_2)) = 0,
\]

\[
\tau_2 u_{L_2}(C_2, L_2) - \beta_{3,k}(w_1(1 - L_1) + T) R w \tau_3 u_{L_2}(R(w_2(1 - L_2) - C_2)) = 0,
\]

and

\[
\left[ \tau_1 u_{L_1}(C_1, L_1) - \tau_1 w_1 u_{C_1}(C_1, L_1) - w_1 \frac{\partial \beta_{2,k}(C_1)}{\partial L_1} [\tau_2 u(C_2, L_2) + \beta_3 \tau_3 u(R(w_2(1 - L_2) - C_2))] \right. \
\left. - w_1 \frac{\partial \beta_{3,k}(C_1)}{\partial L_1} [\beta_{3,k}(C_1) \tau_3 u(R(w_2(1 - L_2) - C_2)) \right] = 0.
\]
As we observe from equations (2.39), (2.40) and (2.41), first period transfers enter as a parameter in all the choice variables of the child. We solve the above problem numerically as a non-linear root finding problem since there is no closed form solution to the child’s problem for any functional form of the utility function. For this purpose we impose the following parametric specification:

\[ u(C,L) = \log(C) + d \frac{L^{1-\gamma}}{1-\gamma} : \text{(Child’s Utility Function)}, \]  
\[ v(C) = \log(C) : \text{(Parent’s Utility Function)}. \]  

(2.42)  
(2.43)

The child’s discount function is given by,

\[ \beta(w_1(1-L_1)+T) = \beta_0 + \frac{1}{1+a(w_1(1-L_1)+T)} \]  
\[ where \ a > 0 \ and \ \beta_0 < 0. \]  

(2.44)

Table 2.6 summarizes the results of the simulations for two alternative scenarios identified by a decrease in the parameter \( \beta_0 \). We observe that as \( \beta_0 \) falls from 0 to -0.01, the parent with a tough love motive lowers transfers to the child. At the same time there is also a fall in the child’s income in the first period corresponding to the fall in \( \beta_0 \).

| \( \eta = 0.5; \ d = 0.5; \ \gamma = 0.7; \ r = 1.02; \ a = 0.01 \) |
|---|---|---|
| \( w_1 = 1; \ w_2 = 2; \ y_p = 2; \ \tau_1 = 5; \ \tau_2 = 40; \ \tau_3 = 20 \) |

<table>
<thead>
<tr>
<th>Optimum</th>
<th>( \beta_0 = 0 )</th>
<th>( \beta_0 = -0.01 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( T^* )</td>
<td>0.6094</td>
<td>0.5354</td>
</tr>
<tr>
<td>Child’s First Period Income</td>
<td>0.9256</td>
<td>0.8543</td>
</tr>
</tbody>
</table>

Table 2.6: Tough Love Altruism Model with Leisure
Thus, in our tough love altruism model the parent’s transfers and the child’s income fall at the same time even though the child is borrowing constrained. Whether or not this feature of our model can explain Altonji, Hayashi and Kotlikoff’s finding is an empirical problem that requires careful study of the PSID data. This depends, among other things, on how income changes are divided into endogenous and exogenous changes. However, the model does imply that the parent’s transfers and the recipient’s income can move in the same direction even when the recipient is borrowing constrained. This can potentially reconcile the apparent inconsistency between empirical results against the redistributive neutrality property and Laitner and Thomas’ (1996) result in favor of parents’ altruism for children. They used TIAA-CREF retirees data and focused on bequests as the channel for parental altruism. They found that for the subsample of respondents characterized by willingness to leave a bequest, the projected amount of the bequest is largest for households with lowest assessments of their children’s likely earnings in the future.

2.7 Conclusion

In the simple setting of a three period economy with a single parent and single child with perfect information and borrowing constraints, we develop a model of intergenerational transfers wherein the tough love motive for parents is a driving force behind the parent’s behavior. In our tough love altruism model, the child’s discount factor is endogenously determined, and the parent evaluates the child’s lifetime utility with a constant discount factor that is higher than that of the child. With our modeling, we try to capture our intuition of tough love: in order to teach his child to be patient, the parent is willing to let the child suffer in the short run. In order to capture this intuition in a simple model, we abstract from the human capital nature of endogenous discounting. We leave this to future research.
The simulation results for the tough love model (for a reasonable range of parameter values) show that as the child becomes more impatient, the parent reacts by cutting down transfers in an attempt to inculcate more patient consumption behavior. This is consistent with our intuition of tough love parenting. The parent with a tough love motive attempts to align the growth rate of the child’s consumption from period 2 to period 3 with the parent’s discount factor, which is assumed in our model to be higher than that of the child. As a result, the slope of consumption of the child from period 2 to period 3 will be too small (either consumption grows too slowly or drops too fast) compared with what the parent prefers. In this case, the parent has a tough love motive to decrease the transfer, so that the child will learn to be more patient thereby increasing the slope. When the child becomes impatient because of an exogenous factor, the slope drops, the tough love motive intensifies, and the transfer decreases. This prediction of our model is in contrast with that of the standard altruism model, in which the parent does not change transfers when the child becomes impatient. Since exogenous changes in the child’s discount factor that make him impatient are likely to cause behavior that calls for the parent’s corrective actions, the tough love altruism model is more consistent with empirical evidence on parental punishments as well as the role of parents in shaping children’s preferences as compared to the standard altruism model.

Another contribution of our paper relates to the empirical evidence against the standard altruism model’s redistributive neutrality property (also called the transfer derivative restriction). Our tough love altruism model also implies redistributive neutrality. However, this redistributive neutrality only holds for exogenous income changes, while in data we can have both endogenous as well as exogenous changes in income. In the version of the tough love altruism model with endogenous leisure choice for the child, we investigate how endogenous changes in income caused by an exogenous change in the child’s discount factor is related to transfers. We find that an exogenous change in the discount factor to make the child more impatient can cause both lower income
and lower transfers from the parent even when the child is borrowing constrained. This prediction of our model may be able to explain the empirical findings by Cox and Altonji, Hayashi and Kotlikoff depending on how income changes are divided into endogenous and exogenous changes among other things.

An important stylized fact for the U.S. economy is that the distribution of wealth is very concentrated and skewed to the right. Castaneda, Diaz-Gimenez, and Rios-Rull (2003) emphasized that standard explanations based on household decision making models with homogeneous preferences fail to account for this observed heterogeneity in the wealth distribution. There is some evidence that heterogeneity in discount factors may be important in understanding differences in savings rates and hence in wealth accumulation. For example, Krusell and Smith (1998) found that incorporation of discount-rate heterogeneity markedly decreases the gap between model predictions and the observed wealth distribution. An interesting feature of our model is that it suggests a pecuniary channel through which parents with tough love motives can instill the virtue of patience in their children. Since not all parents will exhibit such tough love tendencies or the same degree of tough love, our model offers one rationale for individuals discounting future at different rates depending on their parental tough love. To the extent that there is a link between heterogeneity in discount factors and heterogeneity in savings rates, this feature of our model has implications for the observed heterogeneity in wealth in the U.S.

In the future, it will be interesting to analyze the characteristics of parents who exhibit tough love in their children’s upbringing. Bhatt and Ogaki (2009) suggest that the worldview of the parent may be an important factor. For example, how the parent views suffering may be important. If the parent views suffering as meaningless, it is harder for him to let the child suffer. If the parent views suffering as meaningful (e.g., educational), then it is easier for him to let the child suffer.
A new direction for research in this field will be to utilize existing or new survey data on parents’ view on suffering to infer their capacity to exhibit tough love.

In this paper, we have abstracted from the Becker-Mulligan type human capital investment, which increases the discount factor for the child. In the future, it will be interesting to incorporate such an aspect into our tough love model. Another possible extension of our model is to think of a dynasty of tough love altruists where the parent in each generation uses the discount factors he has attained to evaluate the child’s lifetime utility function. In this multi-generational set up a useful generalization will be to allow for heterogeneity in altruistic preferences of the parent. We can think of two types of parental altruistic preferences in the model: one with an endogenous altruism motive and the other with a tough love motive. The parent will act as in the endogenous discounting altruism model if he does not appreciate what the grandparent (his own parent) with a tough love motive did (in the sense we described in Section V), and the parent who appreciates what the grandparent did will act as in the tough love altruism model. This can lead to a model where parents exhibit both tough love and endogenous discounting altruism with some families oscillating between the two types of altruism over generations. The potential usefulness of this extension is that it provides a new theoretical mechanism through which we can obtain heterogeneity in the discount factors across households as an equilibrium outcome, which in turn may help explaining the empirical wealth distribution for the U.S. as discussed earlier.
Chapter 3

CROSS-COHORT DIFFERENCES IN JOINT RETIREMENT: EVIDENCE FROM THE HEALTH AND RETIREMENT STUDY

3.1 Introduction

The increase in the proportion of elderly in the world’s population is one of the most distinctive demographic events in recent times. In the United States, the proportion of population over the age 65 is projected to increase from 12.4% in 2000 to 20.7% in 2050.\(^{33}\) The increased number of persons aged greater than 65 years will potentially lead to higher levels of social insurance and health-care costs. As a result, there are growing concerns about the long run viability of the existing social security, public health care and pension systems. The costs imposed by an aging population will rise more gradually if workers could be persuaded to delay retirement and continue contributing to the social security system. Therefore, the labor force participation (LFP) of older individuals is a major public policy issue with many developed countries introducing policies aimed at delaying retirement.\(^{34}\)

For most of the 20th century the retirement decision was mainly that of the husband’s as few married women spent many years in the labor force. However, as well documented in the literature,

\(^{33}\)Source: U.S. Census Bureau, Census 2000.

\(^{34}\)An example is the increase in the age of eligibility for unreduced retirement benefits in the U.S. from age 65 to 67 with the normal retirement age (NRA) of 67 becoming fully effective for workers who reach age 62 in 2022 or later.
the dramatic rise and sustained participation of women in the labor force since the 1970s implies that increasingly, couples must balance the preferences and constraints of both partners in making retirement decisions. One of the implications of this development is the possibility of an interaction between retirement decisions of spouses, which can lead to coordination in retirement dates of the husband and wife - the phenomenon we call joint retirement. An important question raised by the trend towards increased LFP of older married women is whether this increase has caused the frequency of joint retirement to change over time as more recent cohorts of women become more strongly attached to the labor force and build their own careers. This article studies the extent to which spouses synchronize the timing of their retirements and changes in patterns of retirement across successive cohorts of married women in the U.S.

3.2 Joint Retirement: Extent, Explanations and Relevance

In recent years there has been a growing interest in the retirement behavior of married couples. Hurd (1990) used the New Beneficiary Survey (NBS) data and found that roughly a quarter of married couples retired within a year of one other. Blau (1998) using the Retirement and Health Survey (RHS) data estimated that around 30-40% of couples exited the labor force within 1 year of each other. He also found that the dynamics in participation of one spouse are important to explain transitions by the other spouse. Gustman and Steinmeier (2000) used the National Longitudinal Survey (NLS) of Mature Women and found a significant correlation between the retirement timing of spouses. There is also evidence for joint retirement outcomes from the Health and Retirement Study (HRS) (see Michaud (2003), Coile (2004)).

The observed correlation in the retirement dates of married couples can be explained through various mechanisms. One obvious mechanism is assortative mating in which spouses due to similar
tastes will make similar choices. Another possible mechanism is the correlation in economic variables such as assets, pension incentives, health insurance etc. Financial incentives like employer-provided retiree health insurance may induce couples to retire at the same time (Kapur and Rogowski 2007). Lastly, couples may have correlated preferences over leisure so that time spent together in recreational activities is valued more than time spent alone in such activities. The existing literature on joint retirement suggests that the observed coordination in retirement decisions for married couples seems to be largely explained by the complementarity in leisure preferences of husbands and wives (Blau (1998), Coile (2004)).

Joint retirement is an important issue from a policy perspective. In the presence of interactions in the retirement decisions of spouses, any policy aimed at influencing the retirement outcome of the husband will have indirect effects on the behavior of the wife and vice versa. Ignoring the potential interactions in the retirement decisions of spouses will lead to an underestimation of the true effect of any policy change. Coile (2004) found that there are strong spillover effects generated by retirement incentives of the wife on the retirement decision of the husband. She simulated two changes in social security policy: an increase in the normal retirement age to 67 years and an increase in the delayed retirement credit to 8%, and found that ignoring spillover effects underestimates the effect of the policy on the probability of being in the labor force at age 65 by 13-20%.

3.3 Are Recent Cohorts Less Likely to Retire Together?

The recent increases in older women’s participation can be largely explained by cohort effects (Schirle (2008)). Using the Current Population Survey (CPS) data I plot the age-participation
profiles of married women for selected birth cohorts in Figure 3.1. A rapid transformation in women’s life cycle labor-force participation profiles seems to have occurred between the selected birth cohorts. More pertinent to the present discussion the LFP rates of older married women reflect substantial cohort variation. It can be observed from the figure that for married women born in 1950, participation rates were 22 percentage points higher at age 50 and 24 percentage points higher at age 55 than those of married women born in 1930. In the literature many explanations have been offered for cohort changes in female age-participation profiles. For example, women born in the 1930s and 1940s would have turned 18 a few years before the introduction of the birth control pill in 1960 while those who were born in the 1950s would have had full legal access to the birth control pill. Goldin and Katz (2002) found that, for college women, access to oral contraception led to a later age at first marriage and greater representation of women in professional occupations. Fortin (2005) suggests that changes in individual attitudes towards the role of women have also played an important role in women’s labor market outcomes.

Against this backdrop, one can argue that for couples with wives belonging to more recent cohorts, both spouses would have stronger ties to the labor force. This in turn may make synchronization of retirement decisions more costly as compared to the case for their predecessors. For example, many women today would have accumulated substantial retirement benefits in their own name and hence couples with wives belonging to more recent cohorts need to consider how the retirement decision will impact income and future benefits for both spouses. Given that husbands are on average older than their wives, for many couples, it may not be financially feasible for the wife to follow her husband out of the labor force at a time that simply maximizes his retirement benefits. The objective of this paper is to investigate two related research questions. First, does the incidence of joint retirement amongst married couples exhibit a cohort trend? Second, if there is a
cohort trend, can it be explained by trends in economic factors or does it reflect a change in social norms and preferences for work?

To the best of my knowledge there has been no systematic study comparing different birth cohorts in terms of their likelihood of retiring together or disjointly. An exception is the study by Schellenberg and Ostrovsky (2008) who used the Canadian Longitudinal Administrative Database (LAD) to analyze the retirement patterns of dual-earner couples in which at least one spouse retired in 1986, 1991, 1996 or 2001. They found that between 1986 and 2001 the proportion of dual-earner couples in which both spouses retire within two years of each other declined by two percentage points while the proportion of wives retiring five or more years after their husbands increased by seven percentage points, implying some evidence for increasingly disjointed spousal retirements in Canadian data. However, their results at best provide suggestive evidence on this issue as they only compare cross sections of retiring cohorts at different points in time and hence their results may be confounded by the presence of cohort specific effects.

This paper studies trends in labor force transitions of older married couples with the aim of determining how the incidence of joint retirement has changed across birth cohorts of married women. The analysis is based on labor force status where each spouse can be either employed or not employed in any given period of observation. I define joint retirement to occur when both spouses are employed in one period and both are not employed in the next period. Using the HRS data from 1992-2006 the main finding of this paper is that the likelihood of a married couple jointly exiting the labor force given that both were employed in the previous period decreases

35They define retired individuals as those with annual earnings less than 10% of the average during the previous three years and who remain below that level over the next five years.

36I also used an alternative definition of joint retirement based on self reported retirement status of the respondents in the HRS and found that my main results are not sensitive to this alternative definition of retirement.
across successive birth cohorts of wives (from 1930 through 1950). From a policy perspective, such a trend may mitigate the bias in the estimated retirement policy effect caused by not appropriately accounting for the possible interactions in spousal retirement decisions.

To explain the observed declining cohort trend I estimate a model of labor force exit with a rich set of explanatory variables that include demographic as well as employment characteristics of both spouses. I find that while these factors have substantial explanatory power in explaining variation across households in retirement behavior, trends across cohorts in these factors do not contribute significantly towards explaining the observed cohort trend in joint retirement. This seems to suggest a role for increased individualization of preferences within couples triggered in part by greater preference for work for recent cohorts of workers coupled with women’s increased labor force participation and stronger commitment to work than in the past.

### 3.4 Data and Method

The analysis in this paper is based on data from the HRS, which is a national biennial panel survey of individuals aged 51 and above and their spouses. It provides panel data on demographics, income, assets, health, cognition, family structure and connections, health care utilization and costs, housing, job status and history, expectations, and insurance. The complete HRS includes five cohorts: the HRS cohort (born 1931 to 1941, baseline 1992); the The Study of Assets and Health Dynamics Among the Oldest Old (AHEAD) cohort (born before 1924, baseline 1993); the Children of Depression (CODA) cohort (born 1924 to 1930, added to the study in 1998); the War Baby (WB) cohort (born 1942 to 1947, added to the study in 1998); and finally the Early Baby Boomer (EBB) cohort (born 1948-1953, added to the study in 2004). For the present study, I eliminate the
AHEAD cohort (individuals aged 70 and above in 1993) as most of the members of this cohort would have retired long before 1992. The analysis presented in this paper utilizes information on the remaining four cohorts of the HRS.

**Sample Selection**

I use the first eight waves of the aforesaid four cohorts of the HRS (1992-2006). The data is restricted to observations for which both members of the couple were working full-time in the baseline year and for whom data was non missing for labor force participation, employment characteristics such as the type of pension plan and lastly, health status. In addition, other sample restrictions are imposed driven by the objective of the study. Firstly, I restrict data to couples with enough work history to allow for a reasonable analysis of their labor force transitions. For this purpose I eliminate couples who have less than 10 years of self reported work experience. Secondly, I eliminate couples with more than 15 years of age difference\(^{37}\) between them. This will help in excluding couples who are least likely to be affected by their spouses’ labor supply decisions and hence are not relevant for the present analysis. Thirdly, I restrict my sample to cases where the husband is at least 55 years or older and the wife’s birth year falls between 1930 and 1950. The former condition is imposed as I am interested in studying the retirement behavior of older workers and the latter condition helps to alleviate noise at the tails of the wife’s birth year distribution caused by a lack of sufficient observations at the extreme points of the distribution.\(^{38}\)

\(^{37}\)Age difference is defined as age of the husband minus the wife’s age.

\(^{38}\)It should be noted that the main results of the paper are not sensitive to these sample restrictions. I have conducted the analysis with alternative sets of sample restrictions and obtained qualitatively similar results. While these results are not reported in the paper they are available upon request from the author. I do present the actual as well as model labor force transition probabilities in Appendix B.
The data set for the analysis is structured as couple-year observations. Once any member of the couple retires, the couple exits the data set. The final analysis sample consists of 2085 couples contributing 4972 couple-year observations. The main variable of interest—joint retirement is based on the work status of the husband and the wife. If both move from work for pay to not working for pay between two consecutive waves then they are defined to have jointly retired. The economic factors that may influence joint retirement include a wide range of demographic and employment characteristics. Demographic factors in addition to spouses’ age include indicator variables for the education level, self reported health status and race for both spouses. Employment characteristics include employer provided health insurance (with or without retirement coverage), wage rates and indicator variables for the type of pension plans among others.

Table 3.1 presents weighted means for the sample. The table only reports the means for couple-year observations which is the level of the analysis. In roughly 68% of the observations neither spouse is observed retiring while in 6% of the observations we observe joint retirement. Husbands are on average three years older than their wives and hence are more likely to retire first, though only by one percentage point.\(^3^9\) Table 3.1 also shows that husbands have greater work experience, job tenure and wages compared to their wives. For more than 50% of the observations both spouses have some college or a college degree, more than 90% of the observations is comprised of White/Caucasian couples and roughly 90% of the observations have couples reporting good/very good/excellent health. Finally about half of the husbands are covered by employer provided health insurance (including retiree health insurance) while less than a third of wives have employer provided health insurance, and about half of the couples have some type of pension plan.

\(^3^9\)Based on couple observations, of the included 2085 couples, 14.9% retired jointly, in 29.4% of couples the husband retired first and in 27% of couples the wife retired first.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Retirement Outcome</strong>¹</td>
<td></td>
</tr>
<tr>
<td>Couple Retire Jointly</td>
<td>6.32%</td>
</tr>
<tr>
<td>Husband Retired First</td>
<td>13.11%</td>
</tr>
<tr>
<td>Wife Retired First</td>
<td>12.05%</td>
</tr>
<tr>
<td>Neither Retired</td>
<td>68.52%</td>
</tr>
<tr>
<td><strong>Demographic Characteristics</strong></td>
<td></td>
</tr>
<tr>
<td>Husband’s Age</td>
<td>60.13</td>
</tr>
<tr>
<td>Wife’s Age</td>
<td>57.70</td>
</tr>
<tr>
<td>White/Caucasian</td>
<td>91.85%</td>
</tr>
<tr>
<td>Husband’s Self Reported Health Status²</td>
<td>89.66%</td>
</tr>
<tr>
<td>Wife’s Self Reported Health Status³</td>
<td>91.73%</td>
</tr>
<tr>
<td>Husband had Some College/College</td>
<td>55.92%</td>
</tr>
<tr>
<td>Wife had Some College/College</td>
<td>53.56%</td>
</tr>
<tr>
<td><strong>Employment Characteristics</strong></td>
<td></td>
</tr>
<tr>
<td>Husband Wage</td>
<td>25.98</td>
</tr>
<tr>
<td>Wife Wage</td>
<td>18.33</td>
</tr>
<tr>
<td>Husband Job Tenure</td>
<td>14.08</td>
</tr>
<tr>
<td>Wife Job Tenure</td>
<td>11.54</td>
</tr>
<tr>
<td>Husband Work Experience</td>
<td>41.17</td>
</tr>
<tr>
<td>Wife Work Experience</td>
<td>31.28</td>
</tr>
<tr>
<td>Husband had DB Plan</td>
<td>24.87%</td>
</tr>
<tr>
<td>Wife had DB Plan</td>
<td>25.70%</td>
</tr>
<tr>
<td>Husband has DC Plan</td>
<td>25.40%</td>
</tr>
<tr>
<td>Wife has DC Plan</td>
<td>25.70%</td>
</tr>
<tr>
<td>Husband had Employer Provided HI</td>
<td>48.44%</td>
</tr>
<tr>
<td>Wife had Employer Provided HI</td>
<td>26.15%</td>
</tr>
<tr>
<td>Husband had no Employer Provided HI</td>
<td>32.37%</td>
</tr>
<tr>
<td>Wife had no Employer Provided HI</td>
<td>47.72%</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>4972</td>
</tr>
</tbody>
</table>

1. For couples with both members employed in the previous period.
2. Indicator variable that takes a value of 1 if husband reports good/very good/excellent and 0 otherwise.
3. Indicator variable that takes a value of 1 if wife reports good/very good/excellent and 0 otherwise.

How Often Do Couples Retire Together?

In this subsection I study the dynamics of labor force behavior of married couples to quantify the
frequency of joint exit from the labor force and how it has changed across birth cohorts of wives.
Starting from the initial state of joint employment in the base year, a couple can be in four possible
states the following year- both not employed (joint retirement); husband not employed but wife
employed; husband employed but wife not employed; both employed.

The labor force transition distribution by the wife’s birth year cohort bands are reported in Table
3.2. We can observe that there is a declining cohort trend in the joint retirement outcome. The like-
lihood of moving to state 1 (joint retirement) for a couple with the wife belonging to birth cohort
1945-1950 is about 6.7 percentage points lower than that for a couple with the wife born between
1930-1934. Conditional on at least one spouse retiring, the likelihood of moving to state 1 falls
monotonically from 27.6% for wives born between 1930-1934 to 16.4% for wives born between
1945-1950. On the other hand, the likelihood of moving to state 2 (husband not employed, wife
employed) increased from 26.4% for wives born between 1930-1934 to 48.9% for wives born be-
tween 1945-1950.

This analysis provides some suggestive evidence that the likelihood of jointly exiting the labor
force next period is lower for wives belonging to more recent birth year cohorts. Figure 3.2 plots
the joint retirement outcome across the wife’s birth year from 1930-1950. It uses single year of
birth and supports the finding of Table 3.2: there is a declining wives’ birth cohort trend in the
### Table 3.2: Labor Force Transition from Joint Employment in the base year, by Wife’s Birth Cohort

<table>
<thead>
<tr>
<th>Origin = Both EMPL</th>
<th>Both EMPL</th>
<th>Husband Not EMPL, Wife EMPL</th>
<th>Wife Not EMPL, Husband EMPL</th>
<th>Both Not EMPL</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>1930-1934</td>
<td>69</td>
<td>66</td>
<td>115</td>
<td>381</td>
<td>631</td>
</tr>
<tr>
<td></td>
<td>(10.94%)</td>
<td>(10.46%)</td>
<td>(18.23%)</td>
<td>(60.38%)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[27.60%]</td>
<td>[26.40%]</td>
<td>[46.00%]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1935-1939</td>
<td>112</td>
<td>252</td>
<td>216</td>
<td>1,136</td>
<td>1,716</td>
</tr>
<tr>
<td></td>
<td>(6.53%)</td>
<td>(14.69%)</td>
<td>(12.59%)</td>
<td>(66.20%)</td>
<td></td>
</tr>
<tr>
<td>1940-1944</td>
<td>94</td>
<td>218</td>
<td>186</td>
<td>1,205</td>
<td>1,703</td>
</tr>
<tr>
<td></td>
<td>(5.52%)</td>
<td>(12.80%)</td>
<td>(10.92%)</td>
<td>(70.76%)</td>
<td></td>
</tr>
<tr>
<td>1945-1950</td>
<td>39</td>
<td>116</td>
<td>82</td>
<td>685</td>
<td>922</td>
</tr>
<tr>
<td></td>
<td>(4.23%)</td>
<td>(12.58%)</td>
<td>(8.89%)</td>
<td>(74.30%)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[16.45%]</td>
<td>[48.94%]</td>
<td>[34.61%]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>314</td>
<td>652</td>
<td>599</td>
<td>3,407</td>
<td>4,972</td>
</tr>
</tbody>
</table>

1. Not EMPL= not employed, EMPL= employed.
2. Figures in the parentheses are transition probabilities.
3. Figures in the square brackets are transition probabilities conditional on at least one spouse retiring next period.
Estimating the Cohort Trend in Joint Retirement

Given the evidence for a declining trend in joint retirement as established above, I turn to determine whether the underlying cohort variation in economic factors (that can potentially influence the retirement decision of couples) can explain this trend. If the documented trend in joint retirement can be explained by variations in economic determinants of joint retirement then this cohort trend has little implication for the preference/desire of couples to retire together. They still value leisure time spent together more and hence would like to retire together but the cost of synchronizing retirement dates may rise due to new tradeoffs presented by changes in the economic environment. For example, the increased and sustained labor force participation of recent birth cohorts of women imply that they are better able to contribute to their own pension plans, earn eligibility for Social Security worker benefits, acquire their own health insurance, and build their own net worth. Hence, it may not make much financial sense for wives, who are typically younger than their husbands, to follow their husbands in to retirement and forgo their own future retirement benefits. On the other hand, if economic factors fail to explain the observed trend, then one has to attribute it to changing social norms and preferences about work. For example, changes in social norms about women’s role in the labor market such as a fall in labor market discrimination combined with cohort variations in preference for work (with more recent cohorts having a stronger attachment to their work) may lead to less frequent joint retirement among couples with wives belonging to younger birth cohorts.

40(i) In Figure 3.2, the sudden drop in joint retirement in year 1934 is due to the small sample size in that year in the analysis sample.
(ii) I have restricted my sample to couples with at least 10 years of work experience for both spouses. I have also eliminated couples with greater than 15 years of age difference between them. These restrictions can potentially influence the joint retirement decision of a couple. As a robustness check, I removed these sample selection restrictions and performed the analysis again, but the reported results are not sensitive to the sample selection criteria.
Empirical model

I propose a discrete time, discrete choice model of employment where a couple chooses the LFP of the husband and wife each period to maximize the expected present discounted value (EPDV) of lifetime utility subject to constraints. I define joint retirement based on current work for pay status of the husband and the wife. Each spouse can be employed or not employed, leading to a four-state model as mentioned earlier:

1 = both not employed (Outcome 1)
2 = husband not employed, wife employed (Outcome 2)
3 = wife not employed, husband employed (Outcome 3)
4 = both employed (Outcome 4)

Let subscript $i$ denote the period $t-1$ labor force status of the couple, and subscript $j$ denote the current period ($t$) status. The value of occupying the employment state $j$ in period $t$ is equal to the EPDV of choice $j$ in period $t$ given state $i$ in period $t-1$. I assume that,

$$V_{ijt} \approx X_{ijt}\beta + \epsilon_{ijt} \quad (3.1)$$

where $X_{ijt}$ is a vector of economic factors that may affect a couple’s utility and hence affect the choice in period $t$. A couple will choose $j$ in period $t$ if,

$$V_{ijt} > \max_{k=1-4} V_{ikt} \quad (3.2)$$

If I assume that $\epsilon_{ijt}$ has an i.i.d extreme value distribution then the above framework implies a multinomial logit model (MNL).\(^4\)

\(^4\)An important assumption necessary for obtaining consistent parameter estimates from the MNL specification is that the error terms are independent across alternatives ($\text{Cov}(\epsilon_{ijt}, \epsilon_{ikt}) = 0$). This assumption is also known as the
Many factors can affect the likelihood of a transition from joint employment to any of the four possible states. For example if there is a large positive age gap between the husband and the wife and both have accumulated a substantial enough work history to be eligible for significant retirement benefits, then retiring early to accommodate the husband’s retirement may not be beneficial for the younger wife. Similarly, if one of the spouses retired due to health reasons, then the other spouse may need to continue working (or enter the workforce if not working) to make up for the loss in family income. However, if care giving is important then poor health status of one spouse can encourage joint retirement. Another important factor is the availability of health insurance and whether employer provided health insurance covers the insuree in retirement. Employer provided health insurance is an important source of health care security for older workers who are not eligible for Medicare. Access to retiree health insurance for early retirees through either the husband’s or wife’s employer should increase the propensity to retire jointly. Kapur and Rogowski (2007) find that wives’ retiree health insurance more than doubles the propensity to retire jointly.

Another potential factor affecting the retirement decision of an individual and hence the likelihood of joint retirement is the wage rate. For workers with high wages the opportunity cost of retirement is higher so we would expect high wage workers to be less likely to retire. Similarly, participation in defined benefit (DB) or defined contribution (DC) pension plans can also affect a worker’s decision to retire. In a DB pension plan the pension wealth typically accumulates slowly early in a job, accelerates or jumps after many years of tenure, and then ultimately slows down or declines if one stays in the job long enough. Therefore, DB pensions encourage workers to stay early on in order to gain access to large future pension accruals. In DC pensions, there are no such

Independence of Irrelevant Alternatives (IIA). In the framework proposed above choices of a married couple over different labor force outcomes may fail the independence assumption. Using a Hausman test, I confirm that this assumption is not violated for the estimated MNL model.
spikes in accrual, so the timing of pension wealth accrual is not tied so closely to the timing of retirement as in DB pensions. Friedberg and Webb (2005) found that on average, workers with DB plans retire almost two years earlier as compared to workers with DC plans.

**Explanatory Variables and Estimation Strategy**

The explanatory variables in the model include the age difference between the husband and the wife, indicator variables for the level of education of each spouse, race and health status of each spouse. I define five indicator variables based on five categories of education for both spouses: high school drop outs, GED, high school graduates, some college and college and treat GED as the excluded category. Race is captured by indicator variables for White and Black with the excluded category being the other race groups. I define the health status of the husband as an indicator variable that takes value 1 if the husband is in good health based on self reports of fair or poor health. The health status of the wife is defined analogously. To capture the effect of health insurance on joint labor supply I include an indicator variable for the husband having retiree health insurance offered through his own employer and an indicator for the husband having no employer provided health insurance through his own employer. The omitted category is the husband having employer provided health insurance but no coverage in retirement. Health insurance indicators for the wife are defined analogously. I also include job characteristics. These include the hourly wage rate, indicator variables for pension types, work experience, job tenure, and indicator variables for industry and occupation.

The estimation strategy I adopt in this paper is to first estimate a specification in which the wife’s birth year cohort dummy variables (from 1931 through 1950) are the only explanatory variables. I then add the other controls and determine whether their inclusion reduces the influence of
the cohort dummy variables. If there is an economic explanation for the observed declining cohort trend in joint retirement then we would expect the effect of the cohort dummy variables to dissipate after the inclusion of the economic factors. Formally, the hypothesis that I wish to test is:

\[ H_0 : \beta_{1931} = \beta_{1932} = \ldots = \beta_{1950} = 0 \iff \text{Economic Factors Explain the Cohort Trend} \]

### 3.5 Estimation Results

**How do economic and demographic factors influence labor force transitions?**

I report the marginal effects for selected demographic and employment characteristics from the estimated MNL in Table 3.3. As expected I find that better health of the wife lowers the likelihood of outcome 1 (joint retirement) as well as outcome 3 (wife retires first) and increases the likelihood of outcome 4 (both stay employed). Similarly better health of the husband lowers the likelihood of outcome 1 and outcome 2 (husband retires first) and increases the likelihood of outcome 4.

An increase in the age difference between the husband and the wife makes coordination of retirement dates harder, with the incidence of the husband retiring first more likely and the incidence of the wife retiring first less likely. Consistent with this we find that greater age differences lowers the likelihood of the wife retiring first while it increases the likelihood of the husband retiring first. It also lowers the likelihood of joint retirement and joint employment but the former effect is not statistically significant.

DB plan participation by the husband increases the likelihood of joint retirement and lowers the likelihood of joint employment. DC plan participation by the wife lowers the likelihood of the wife retiring first. Since DB plan participation is more likely to predict early retirement than the DC plan these results seem to be in the right direction. On the other hand, DB plan participation
by the wife as well as DC plan participation by the husband do not enter significantly in any of the outcome choices.

Access to health insurance (HI) in retirement for both spouses lowers the likelihood of both spouses staying in the labor force. For the wife, availability of retiree HI increases the likelihood of her retiring first and analogously the access to retiree HI for the husband increases the likelihood of his retiring first. These results are in line with our expectation as health insurance coverage should incentivize early retirement for both spouses. Job characteristics like tenure, experience, wages, industry and occupation (not reported) have very small effects on the likelihood of any outcome and are insignificant in most cases.
<table>
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<th>Variable</th>
<th>Both Retired</th>
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<th>Only Husband Retired</th>
<th></th>
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<td>Age Difference</td>
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<td>0.0100</td>
<td>-0.0909</td>
<td>0.0117</td>
<td>0.0130</td>
<td>0.0156</td>
<td>0.0964</td>
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<tr>
<td>Wife in Good Health</td>
<td>-0.0247</td>
<td>0.0105</td>
<td>-0.0044</td>
<td>0.0148</td>
<td>-0.0718</td>
<td>0.0144</td>
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<td>0.0207</td>
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<td>Husband had DB</td>
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<td>Wife had DB</td>
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<td>Wife had DC</td>
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<td>Husband had Retire HI</td>
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<td>0.0030</td>
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<td>0.0201</td>
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<td>0.0049</td>
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<td>-0.0402</td>
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<tr>
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<td>0.1091</td>
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<td>1937</td>
<td>-0.0440**</td>
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<td>0.1605</td>
<td>0.1120</td>
<td>-0.0423</td>
<td>0.0285</td>
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<td>0.0976</td>
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<tr>
<td>1938</td>
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<td>0.0860</td>
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<td>-0.0449†</td>
<td>0.0272</td>
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<td>1939</td>
<td>-0.0421**</td>
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<td>0.1198</td>
<td>0.1038</td>
<td>-0.0572*</td>
<td>0.0242</td>
<td>-0.0205</td>
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<td>1940</td>
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<td>-0.0539*</td>
<td>0.0250</td>
<td>0.0038</td>
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</tbody>
</table>

Continued on the next page...

†p<.10; *p<.05; **p<.01

Table 3.3: Selected Marginal Effects from Multinominal Logit Model of Joint Retirement

74
Table 3.3 Continued....

<table>
<thead>
<tr>
<th>Variable</th>
<th>Both Retired</th>
<th>Only Husband Retired</th>
<th>Only Wife Retired</th>
<th>Neither Retired</th>
</tr>
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<tbody>
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<td>1944</td>
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<td>0.0119</td>
<td>0.0648</td>
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<td>0.0071</td>
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<td>0.0939</td>
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<td>0.1181</td>
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<td>1950</td>
<td>-0.0489**</td>
<td>0.0134</td>
<td>-0.0680</td>
<td>0.0545</td>
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</table>

Number of Observations: 4972
Log Likelihood: -4363.20
Psuedo R2: 0.081

Wald test of Joint Significance of Birth Cohort Dummies: 109.04

1. Standard errors are clustered by couple to account for unknown within-couple correlation in errors.
2. Terms in the square bracket is the p-value of the Wald test.
3. The model includes all the variables discussed on pages 13-14. Only selected marginal effects are reported here. Each equation includes indicator variables for both spouses’ industry, occupation, education and race.
4. HI=Health Insurance, EPHI=Employer Provided HI.

†p<.10; *p<.05; **p<.01
Significance of the Cohort Trend

If the included economic and demographic factors could explain the observed trend in the joint retirement outcome, we should expect that the indicator variables for the wife’s birth year should be jointly insignificant in the joint retirement equation. From Table 3.3, based on the Wald test of the null hypothesis (of the joint insignificance of the wife’s birth year indicators) we can reject the null hypothesis at any conventional level of significance. Hence, even after controlling for economic factors the declining cohort trend in joint retirement remains significant. To illustrate the significance of the cohort trend I use the model estimates presented in Table 3.3 to compute the predicted transition probabilities evaluated at the mean value of all included covariates and plot them against the birth years of wives. Figure 3.3 through Figure 3.6 presents the cohort trend in four joint labor supply outcomes with and without controlling for the explanatory variables. The trend without explanatory variables reproduces the raw data shown in Figure 3.1. Firstly, from Figure 3.3 we observe that there is a declining trend in predicted joint retirement (Outcome 1). Further, holding the explanatory variables constant at their mean values explains only a small part of this declining trend. Secondly, from Figure 3.6 there seems to be a rising trend in Outcome 4 (both spouses continue working). However, this pattern could be a result of the fact that couples with the wives’ belonging to younger cohorts are too young to retire by 2006 (the last year of observation in HRS). To examine this, Figure 3.7 through Figure 3.9 plots the mean predicted outcomes conditional on at least one member of the couple retiring. I compute the conditional mean predicted outcome \( i = 1, 2, 3 \) (labor force states) using the following expression:

$$\text{Mean predicted outcome } i = \frac{\pi(i)}{\pi(1)+\pi(2)+\pi(3)}$$
where $\pi(i)$ is the predicted outcome $i$ from the MNL estimation. I find that the declining cohort trend in joint retirement is paralleled by a rising cohort trend in Outcome 2 (husband retiring first) (see Figures 3.7 and 3.8). This was not apparent in figures 3.3 through 3.6 indicating the importance of accounting for the relatively young age of the more recent birth cohorts as of the last survey in 2006.

3.6 Conclusion

The analysis in this article shows that there are significant cohort trends in the retirement transitions of married couples in the U.S. Specifically, there is a significant and declining trend in the likelihood of joint retirement, and conditional on at least one spouse retiring, this trend seems to be accounted for by the rising cohort trend in the incidence of the husband retiring first. A MNL model of joint retirement is estimated to explain this trend using a wide range of economic factors as explanatory variables. I find that the declining trend in joint retirement cannot be explained by simply accounting for underlying trends in economic factors influencing the retirement decision of couples. One way to interpret this result is to argue that while demographic and employment characteristics of husbands and wives reasonably explain retirement transitions over a cross section of married couples, they have little explanatory power when it comes to explaining the observed cohort trend in joint retirement. The results seem to indicate that the observed cohort trend could be a result of changes in non-economic factors making recent cohorts of married couples less likely to coordinate their retirement timings. For example, there is some evidence that recent cohorts of workers are more likely to work at older ages and this can be explained by greater preference for work of these cohorts (see Maestas, 2007). Such cross-cohort changes in preferences coupled with greater labor force attachment of married women belonging to more recent cohorts can explain, for example, why these women (typically two to three years younger than their husbands), may
not follow their husbands into retirement.

With the imminent retirement of the baby boom generation, much discussion focuses on how older workers might be encouraged to stay in the labor force. In the presence of interactions in the retirement decisions of spouses, any policy aimed at influencing the retirement outcome of the husband will have indirect effects on the behavior of the wife and vice versa. Ignoring the potential interactions in the retirement decisions of spouses will lead to underestimation of the true effect of the policy change (Coile (2004)). An important implication of the results presented in this paper is that the ‘bias’ in measuring the effect of a retirement policy (such as a change in normal retirement age) caused by ignoring interactions in spousal retirement decisions can be mitigated by the increasingly independent manner in which spouses in dual-earner couples appear to be retiring.
Figure 3.1: Age-Participation Profile for Selected Cohort of Married Women (Source: Author’s Calculation from IPUMS-CPS Data)
Figure 3.2: Cohort Trend in Joint Retirement
Figure 3.3: Probability of Both Exiting the Labor Force by Wife’s Birth Cohort
Figure 3.4: Probability of Only Husband Exiting the Labor Force by Wife’s Birth Cohort
Figure 3.5: Probability of Only Wife Exiting the Labor Force by Wife’s Birth Cohort
Figure 3.6: Probability of No One Exiting the Labor Force by Wife’s Birth Cohort
Figure 3.7: Probability of BothExiting the Labor Force by Wife’s Birth Cohort, Conditional on at least One Spouse Retiring
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<th>Year</th>
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<th>Predicted</th>
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<tr>
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<td>0.99</td>
<td>0.98</td>
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<td>1950</td>
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Figure 3.8: Probability of Only Husband Exiting the Labor Force by Wife’s Birth Cohort, Conditional on at least One Spouse Retiring
Figure 3.9: Probability of Only Wife Exiting the Labor Force by Wife’s Birth Cohort, Conditional on at least One Spouse Retiring
BIBLIOGRAPHY


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Madden, G. J., Petry, N., Badger, G. and Bickel, W. K. 1997.“Impulsive and Self-Control Choices in Ppionoi-Dependent Subjects and Non-Drug Using Control: Drug and Monetary Rewards”.

*Experimental and Clinical Psychopharmacology* 5 : 256-262.


Appendix A

APPENDIX FOR CHAPTER 2

A.1 Redistributive Neutrality in Tough Love Altruism Model

Consider the parent’s maximization program in the tough love model:

\[
\max_T \left[ \eta v(y_p - T) + (1 - \eta) \left[ u(y_1 + T) + \beta_{2,p} u(C_2^*) \right. \right.
\]
\[
\left. + \beta_{2,p} \beta_{3,p} u(R(y_2 - C_2^*)) \right] \right)
\]
(A.1)

where,

\[
\{C_2^*\} \equiv \arg \max_{C_2} \left[ u(C_2) + \beta_{3,k}(y_1 + T) u(R(y_2 - C_2)) \right]
\]
(A.2)

Now from the first order condition of the child’s maximization problem,

\[
u_{C_2}(C_2) - \beta_{3,k}(y_1 + T) R u_{C_2}(R(y_2 - C_2)) = 0
\]
(A.3)

Then using the implicit function theorem we get,

\[C_2^* = C_2(y_2, y_1 + T, R)\]
(A.4)

In this wealth redistribution experiment we only change \(y_p\) and \(y_1\). Hence we can treat \(R\) and \(y_2\) as constants. Also note that from child’s first period borrowing constraint,

\[C_1 = y_1 + T\]
(A.5)
Using these facts, we can rewrite child’s optimal period 2 consumption as,

\[ C_2^* = C_2(C_1) \]  
(A.6)

Substituting child’s optimal second period consumption in the parent’s problem we get,

\[
\begin{align*}
\text{Max}_{T} & \quad \eta v(y_p - T) + (1 - \eta) \left[ u(y_1 + T) + \beta_{2,p}u(C_2(C_1)) \right] \\
& \quad + \beta_{2,p}\beta_{3,p}u(R(y_2 - C_2(C_1))) 
\end{align*}
\]  
(A.7)

Define \( C_p = y_p - T \) for notational simplicity. Then the first order condition for the parent’s problem is,

\[
\begin{align*}
- \eta v'(C_p) + (1 - \eta) \left[ u'(C_1) + \beta_{2,p}u'(C_2(C_1))C_2'(C_1) - \beta_{2,p} \right. \\
& \quad \left. \beta_{3,p}Ru'(R(y_2 - C_2(C_1)))C_2'(C_1) \right] = 0 
\end{align*}
\]  
(A.8)

Now we totally differentiate equation (A.8) assuming \( R, y_2, \beta_{2,p} \) and \( \beta_{3,p} \) are constants. We get,

\[
\begin{align*}
- \eta v''(C_p)dy_p + \eta v''(C_p)dT + (1 - \eta) \left[ u''(C_1)dy_1 + u''(C_1)dT + \beta_{2,p}u''(C_2(C_1))C_2''(C_1)dy_1 + \beta_{2,p}u''(C_2(C_1))C_2''(C_1)dT \\
& \quad + \beta_{2,p}\beta_{3,p}Ru''(R(y_2 - C_2(C_1)))C_2''(C_1)dy_1 + \beta_{2,p}\beta_{3,p}R^2u''(R(y_2 - C_2(C_1)))C_2''(C_1)dT \\
& \quad + \beta_{2,p}\beta_{3,p}Ru'(R(y_2 - C_2(C_1)))C_2''(C_1)dy_1 + \beta_{2,p}\beta_{3,p}Ru'(R(y_2 - C_2(C_1)))C_2''(C_1)dT \right] = 0 
\end{align*}
\]  
(A.9)

From equation (A.9) it is straightforward to show that,

\[
\frac{\partial T^*}{\partial y_p} = \frac{\eta v''(C_p)}{A1} \]  
(A.10)

\[
\frac{\partial T^*}{\partial y_1} = -\frac{A2}{A1} \]  
(A.11)
where

\[ A1 \equiv \eta v''(C_p) + (1 - \eta) \left[ u''(C_1) + \beta_{2,p}u''(C_2(C_1))C_2'(C_1)^2 + \beta_{2,p}u'(C_2(C_1))C_2''(C_1) + \beta_{2,p}\beta_{3,p}R^2u''(R(y_2 - C_2(C_1)))C_2'(C_1) + \beta_{2,p}\beta_{3,p}Ru'(R(y_2 - C_2(C_1)))C_2''(C_1) \right] \tag{A.12} \]

and

\[ A2 \equiv (1 - \eta) \left[ u''(C_1) + \beta_{2,p}u''(C_2(C_1))C_2'(C_1)^2 + \beta_{2,p}u'(C_2(C_1))C_2''(C_1) + \beta_{2,p}\beta_{3,p}R^2u''(R(y_2 - C_2(C_1)))C_2'(C_1) + \beta_{2,p}\beta_{3,p}Ru'(R(y_2 - C_2(C_1)))C_2''(C_1) \right] \tag{A.13} \]

Hence,

\[ \frac{\partial T^*}{\partial y_p} - \frac{\partial T^*}{\partial y_1} = \frac{\eta v''(C_p) + A2}{A1} = \frac{A1}{A1} = 1 \Rightarrow Redistributive \ Neutral \ity \tag{A.14} \]

**A.2 Redistributive Neutrality in Endogenous Altruism Model**

Consider the parent’s maximization program in the endogenous altruism model:

\[
\max_T \left[ \eta v(y_p - T) + (1 - \eta) \left[ u(y_1 + T) + \beta_{2,p}(y_1 + T)u(C_2^*) + \beta_{2,p}(y_1 + T)\beta_{3,p}(y_1 + T)u(R(y_2 - C_2^*)) \right] \right] \tag{A.15}
\]

where,

\[ \{C_2^*\} \equiv \arg \max_{C_2} \left[ u(C_2) + \beta_{3,k}(y_1 + T)u(R(y_2 - C_2)) \right] \tag{A.16} \]

From the first order condition for the child’s problem we get:

\[ u_{C_2}(C_2) - \beta_{3,k}(y_1 + T)Ru_{C_2}(R(y_2 - C_2)) = 0 \tag{A.17} \]
Using the *implicit function theorem* we get,

\[ C_2^* = C_2(y_2, \beta_{3,k}(y_1 + T), R) \]  
(A.18)

In this wealth redistribution experiment we only change \( y_p \) and \( y_1 \). Hence we can treat \( R \) and \( y_2 \) as constants. Also note that from child’s first period borrowing constraint,

\[ C_1 = y_1 + T \]  
(A.19)

Using these facts, we can rewrite child’s optimal period 2 consumption as,

\[ C_2^* = C_2(C_1) \]  
(A.20)

Substituting child’s optimal second period consumption in the parent’s problem we get,

\[
\max_T \left[ \eta v(C_p) + (1 - \eta) \left( u(C_1) + \beta_{2,p}(C_1)u(C_2(C_1)) + \beta_{2,p}(C_1)\beta_{3,p}(C_1)u(R(y_2 - C_2(C_1))) \right) \right] = 0
\]  
(A.21)

where,

\[ C_p = y_p - T \]

\[ C_1 = y_1 + T \]  
(A.22)

F.O.C for the parent’s problem,

\[
\begin{align*}
-\eta v'(C_p) + (1 - \eta) \left[ u'(C_1) + \beta_{2,p}'(C_1)u(C_2(C_1)) + \beta_{2,p}'(C_1)u'(C_2(C_1))C_2'(C_1) \
+ \beta_{2,p}'(C_1)\beta_{3,p}'(C_1)u(R(y_2 - C_2(C_1))) + \beta_{2,p}'(C_1)\beta_{3,p}'(C_1)'u(R(y_2 - C_2(C_1))) \
- R\beta_{2,p}'(C_1)\beta_{3,p}'(C_1)u'(R(y_2 - C_2(C_1)))C_2'(C_1) \right] &= 0
\end{align*}
\]  
(A.23)
Now we totally differentiate equation (A.23) assuming $R$ and $y_2$ are constants. We get,

$$\begin{align*}
\left[ -\eta v''(C_p)dy_p + \eta v''(C_p)dt + (1-\eta) \left[ u''(C_1) + \beta_{2,p}''(C_1)u(C_2(C_1)) + 2\beta_{2,p}''(C_1)u'(C_2(C_1))C_2'(C_1) \\
+ \beta_{2,p}(C_1)u''(C_2(C_1))C_2'(C_1)^2 + \beta_{2,p}(C_1)u'(C_2(C_1))C_2''(C_1) + \beta_{2,p}''(C_1)\beta_{3,p}(C_1)u(R(y_2 - C_2(C_1))) \\
+ 2\beta_{2,p}'(C_1)\beta_{3,p}'(C_1)u(R(y_2 - C_2(C_1))) - R\beta_{2,p}'(C_1)\beta_{3,p}(C_1)u'(R(y_2 - C_2(C_1)))C_2'(C_1) \\
+ \beta_{2,p}(C_1)\beta_{3,p}''(C_1)u(R(y_2 - C_2(C_1))) - R\beta_{2,p}'(C_1)\beta_{3,p}'(C_1)u'(R(y_2 - C_2(C_1)))C_2''(C_1) \\
+ R^2\beta_{2,p}'(C_1)\beta_{3,p}'(C_1)u(R(y_2 - C_2(C_1)))C_2'(C_1)^2 - R\beta_{2,p}'(C_1)\beta_{3,p}(C_1)u'(R(y_2 - C_2(C_1)))C_2''(C_1) \\
- R\beta_{2,p}'(C_1)\beta_{3,p}(C_1)u'(R(y_2 - C_2(C_1)))C_2'(C_1) \\
- R\beta_{2,p}'(C_1)\beta_{3,p}'(C_1)u'(R(y_2 - C_2(C_1)))C_2''(C_1) \right] (dy_1 + dt) \right] = 0
\end{align*}$$

(A.24)

From equation (A.24) it is straightforward to show that,

$$\frac{\partial T^*}{\partial y_p} = \frac{\eta v''(C_p)}{A1}$$

(A.25)

$$\frac{\partial T^*}{\partial y_1} = -\frac{A2}{A1}$$

(A.26)

where,

$$A1 \equiv \eta v''(C_p) + (1-\eta) \left[ u''(C_1) + \beta_{2,p}''(C_1)u(C_2(C_1)) + 2\beta_{2,p}''(C_1)u'(C_2(C_1))C_2'(C_1) \\
+ \beta_{2,p}(C_1)u''(C_2(C_1))C_2'(C_1)^2 + \beta_{2,p}(C_1)u'(C_2(C_1))C_2''(C_1) \\
+ \beta_{2,p}''(C_1)\beta_{3,p}(C_1)u(R(y_2 - C_2(C_1))) + 2\beta_{2,p}'(C_1)\beta_{3,p}'(C_1)u(R(y_2 - C_2(C_1))) \\
- R\beta_{2,p}'(C_1)\beta_{3,p}(C_1)u'(R(y_2 - C_2(C_1)))C_2'(C_1) + \beta_{2,p}(C_1)\beta_{3,p}''(C_1)u(R(y_2 - C_2(C_1))) \\
- R\beta_{2,p}'(C_1)\beta_{3,p}'(C_1)u'(R(y_2 - C_2(C_1)))C_2'(C_1) \\
+ R^2\beta_{2,p}'(C_1)\beta_{3,p}'(C_1)u(R(y_2 - C_2(C_1)))C_2'(C_1)^2 - R\beta_{2,p}'(C_1)\beta_{3,p}(C_1)u'(R(y_2 - C_2(C_1)))C_2''(C_1) \\
- R\beta_{2,p}'(C_1)\beta_{3,p}'(C_1)u'(R(y_2 - C_2(C_1)))C_2''(C_1) \right]$$

(A.27)
\[ A2 \equiv (1 - \eta) \left[ u''(C_1) + \beta''_{2,p}(C_1)u(C_2(C_1)) + 2\beta_{2,p}(C_1)u'(C_2(C_1))C_2'(C_1) \right. \\
+ \beta_{2,p}(C_1)u''(C_2(C_1))C_2'(C_1)^2 + \beta_{2,p}(C_1)u'(C_2(C_1))C_2''(C_1) \\
+ \beta''_{2,p}(C_1)\beta_{3,p}(C_1)u(R(y_2 - C_2(C_1))) + 2\beta_{2,p}(C_1)\beta_{3,p}(C_1)u(R(y_2 - C_2(C_1))) \\
- R\beta'_{2,p}(C_1)\beta_{3,p}(C_1)u'(R(y_2 - C_2(C_1)))C_2'(C_1) + \beta_{2,p}(C_1)\beta''_{3,p}(C_1)u(R(y_2 - C_2(C_1))) \\
- R\beta_{2,p}(C_1)\beta_{3,p}(C_1)u'(R(y_2 - C_2(C_1)))C_2'(C_1) + R^2\beta_{2,p}(C_1)\beta_{3,p}(C_1)u''(R(y_2 - C_2(C_1)))C_2'(C_1)^2 \\
- R\beta_{2,p}(C_1)\beta_{3,p}(C_1)u'(R(y_2 - C_2(C_1)))C_2''(C_1) - R\beta''_{2,p}(C_1)\beta_{3,p}(C_1)u'(R(y_2 - C_2(C_1)))C_2'(C_1) \\
\left. - R\beta_{2,p}(C_1)\beta''_{3,p}(C_1)u'(R(y_2 - C_2(C_1)))C_2'(C_1) \right] \]

Hence,

\[
\frac{\partial T^*}{\partial y_p} - \frac{\partial T^*}{\partial y_1} = \eta u''(C_p) + A2 = \frac{A1}{A1} = 1 
\]

\( \Leftrightarrow \) Redistributive Neutrality

(A.28)
A.3 Simulation Results for Tough Love Altruism Model with alternative assumption about parameters

**Global Parameters**

$\eta = 0.5; \sigma = 1.5; R = 1.2;
\beta_p = 1; y_1 = 2; y_2 = 10; y_p = 10; a = 0.03$

<table>
<thead>
<tr>
<th>Optimum</th>
<th>$\beta_0 = 0$</th>
<th>$\beta_0 = -0.4$</th>
<th>$\beta_0 = -0.6$</th>
<th>$\beta_0 = -0.8$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T^*$</td>
<td>3.9824</td>
<td>3.8388</td>
<td>3.5101</td>
<td>1.8516</td>
</tr>
<tr>
<td>$C_1^*$</td>
<td>5.9824</td>
<td>5.8388</td>
<td>5.5101</td>
<td>3.8516</td>
</tr>
<tr>
<td>$C_2^*$</td>
<td>5.4260</td>
<td>6.4376</td>
<td>7.2384</td>
<td>8.3481</td>
</tr>
<tr>
<td>$C_3^*$</td>
<td>5.4888</td>
<td>4.2749</td>
<td>3.3139</td>
<td>1.9822</td>
</tr>
<tr>
<td>$\beta(C_1^*)$</td>
<td>0.8478</td>
<td>0.4509</td>
<td>0.2581</td>
<td>0.0964</td>
</tr>
</tbody>
</table>

Table A.1: Tough Love Altruism Model ($\sigma > 1$)

**Global Parameters**

$\eta = 0.5; \sigma = 4; R = 1.2;
\beta_p = 1; y_1 = y_2 = 3; y_p = 5; a = 0.01$

<table>
<thead>
<tr>
<th>Optimum</th>
<th>$\beta_0 = 0$</th>
<th>$\beta_0 = -0.4$</th>
<th>$\beta_0 = -0.6$</th>
<th>$\beta_0 = -0.8$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T^*$</td>
<td>0.9986</td>
<td>0.9646</td>
<td>0.8990</td>
<td>0.5718</td>
</tr>
<tr>
<td>$C_1^*$</td>
<td>3.9986</td>
<td>3.9646</td>
<td>3.8990</td>
<td>3.5718</td>
</tr>
<tr>
<td>$C_2^*$</td>
<td>1.6097</td>
<td>1.7093</td>
<td>1.7892</td>
<td>1.9276</td>
</tr>
<tr>
<td>$C_3^*$</td>
<td>1.6683</td>
<td>1.5489</td>
<td>1.4530</td>
<td>1.2868</td>
</tr>
<tr>
<td>$\beta(C_1^*)$</td>
<td>0.9616</td>
<td>0.5619</td>
<td>0.3625</td>
<td>0.1655</td>
</tr>
</tbody>
</table>

Table A.2: Tough Love Altruism Model ($\sigma > 1$)
### Global Parameters

\[
\begin{align*}
\eta &= 0.2; \sigma = 1.5; R = 1.2; \\
\beta_p &= 1; y_1 = y_2 = 3; y_p = 5; a = 0.01
\end{align*}
\]

<table>
<thead>
<tr>
<th>Optimum</th>
<th>(\beta_0 = 0)</th>
<th>(\beta_0 = -0.4)</th>
<th>(\beta_0 = -0.6)</th>
<th>(\beta_0 = -0.8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(T^*)</td>
<td>2.7251</td>
<td>2.6883</td>
<td>2.6165</td>
<td>2.2024</td>
</tr>
<tr>
<td>(C_1^*)</td>
<td>5.7251</td>
<td>5.6883</td>
<td>5.6165</td>
<td>5.2024</td>
</tr>
<tr>
<td>(C_2^*)</td>
<td>1.5734</td>
<td>1.8419</td>
<td>2.0484</td>
<td>2.3691</td>
</tr>
<tr>
<td>(C_3^*)</td>
<td>1.7120</td>
<td>1.3898</td>
<td>1.1419</td>
<td>0.7571</td>
</tr>
<tr>
<td>(\beta(C_1^*))</td>
<td>0.9458</td>
<td>0.5462</td>
<td>0.3468</td>
<td>0.1505</td>
</tr>
</tbody>
</table>

Table A.3: Tough Love Altruism Model (\(\sigma > 1\))

### Global Parameters

\[
\begin{align*}
\eta &= 0.8; \sigma = 1.5; R = 1.2; \\
\beta_p &= 1; y_1 = 2; y_2 = 10; y_p = 10; a = 0.01
\end{align*}
\]

<table>
<thead>
<tr>
<th>Optimum</th>
<th>(\beta_0 = 0)</th>
<th>(\beta_0 = -0.4)</th>
<th>(\beta_0 = -0.6)</th>
<th>(\beta_0 = -0.8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(T^*)</td>
<td>1.4088</td>
<td>1.3956</td>
<td>1.3720</td>
<td>1.2640</td>
</tr>
<tr>
<td>(C_1^*)</td>
<td>3.4088</td>
<td>3.3956</td>
<td>3.3720</td>
<td>3.2640</td>
</tr>
<tr>
<td>(C_2^*)</td>
<td>5.2077</td>
<td>6.0799</td>
<td>6.7444</td>
<td>7.7703</td>
</tr>
<tr>
<td>(C_3^*)</td>
<td>5.7508</td>
<td>4.7042</td>
<td>3.9067</td>
<td>2.6757</td>
</tr>
<tr>
<td>(\beta(C_1^*))</td>
<td>0.9670</td>
<td>0.5672</td>
<td>0.3674</td>
<td>0.1684</td>
</tr>
</tbody>
</table>

Table A.4: Tough Love Altruism Model (\(\sigma > 1\))

### Global Parameters

\[
\begin{align*}
\eta &= 0.5; \sigma = 0.7; R = 1.2; \\
\beta_p &= 1; y_1 = 2; y_2 = 10; y_p = 10; a = 0.03
\end{align*}
\]

<table>
<thead>
<tr>
<th>Optimum</th>
<th>(\beta_0 = 0)</th>
<th>(\beta_0 = -0.4)</th>
<th>(\beta_0 = -0.6)</th>
<th>(\beta_0 = -0.8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(T^*)</td>
<td>3.9257</td>
<td>3.4226</td>
<td>2.7336</td>
<td>1.2040</td>
</tr>
<tr>
<td>(C_1^*)</td>
<td>5.9257</td>
<td>5.4226</td>
<td>4.7336</td>
<td>3.2040</td>
</tr>
<tr>
<td>(C_2^*)</td>
<td>5.3882</td>
<td>7.3710</td>
<td>8.5355</td>
<td>9.5459</td>
</tr>
<tr>
<td>(C_3^*)</td>
<td>5.5341</td>
<td>3.1548</td>
<td>1.7574</td>
<td>0.5450</td>
</tr>
<tr>
<td>(\beta(C_1^*))</td>
<td>0.8491</td>
<td>0.4601</td>
<td>0.2756</td>
<td>0.1123</td>
</tr>
</tbody>
</table>

Table A.5: Tough Love Altruism Model (\(\sigma < 1\))
### Global Parameters

$\eta = 0.2; \sigma = 0.7; R = 1.2; \beta_p = 1; y_1 = y_2 = 3; y_p = 5; a = 0.01$

<table>
<thead>
<tr>
<th>Optimum</th>
<th>$\beta_0 = 0$</th>
<th>$\beta_0 = -0.4$</th>
<th>$\beta_0 = -0.6$</th>
<th>$\beta_0 = -0.8$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T^*$</td>
<td>4.0273</td>
<td>3.9917</td>
<td>3.9388</td>
<td>3.7636</td>
</tr>
<tr>
<td>$C_1^*$</td>
<td>7.0273</td>
<td>6.9917</td>
<td>6.9388</td>
<td>6.7636</td>
</tr>
<tr>
<td>$C_2^*$</td>
<td>1.5142</td>
<td>2.0804</td>
<td>2.4454</td>
<td>2.8223</td>
</tr>
<tr>
<td>$C_3^*$</td>
<td>1.7830</td>
<td>1.1035</td>
<td>0.6655</td>
<td>0.2132</td>
</tr>
<tr>
<td>$\beta(C_1^*)$</td>
<td>0.9343</td>
<td>0.5347</td>
<td>0.3351</td>
<td>0.1366</td>
</tr>
</tbody>
</table>

Table A.6: Tough Love Altruism Model ($\sigma < 1$)

### Global Parameters

$\eta = 0.8; \sigma = 0.7; R = 1.2; \beta_p = 1; y_1 = 1; y_2 = 10; y_p = 15; a = 0.01$

<table>
<thead>
<tr>
<th>Optimum</th>
<th>$\beta_0 = 0$</th>
<th>$\beta_0 = -0.4$</th>
<th>$\beta_0 = -0.6$</th>
<th>$\beta_0 = -0.8$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T^*$</td>
<td>0.9395</td>
<td>0.9021</td>
<td>0.8533</td>
<td>0.7367</td>
</tr>
<tr>
<td>$C_1^*$</td>
<td>1.9395</td>
<td>1.9021</td>
<td>1.8533</td>
<td>1.7367</td>
</tr>
<tr>
<td>$C_2^*$</td>
<td>4.8733</td>
<td>6.6747</td>
<td>7.8539</td>
<td>9.1282</td>
</tr>
<tr>
<td>$C_3^*$</td>
<td>6.1521</td>
<td>3.9904</td>
<td>2.5753</td>
<td>1.0462</td>
</tr>
<tr>
<td>$\beta(C_1^*)$</td>
<td>0.9810</td>
<td>0.5813</td>
<td>0.3818</td>
<td>0.1829</td>
</tr>
</tbody>
</table>

Table A.7: Tough Love Altruism Model ($\sigma < 1$)
B.1 Robustness checks for alternative sets of sample restrictions

In the paper I have restricted sample to couples where husband’s age $\geq 55$ years, age difference between husband and wife is $\leq 15$ years and lastly both spouses have work experience $\geq 10$ years. This leads to my analysis sample of 2085 couples contributing 4972 couple-year observations. As mentioned in footnotes 6 and 8 of the paper, the main results of the paper are not sensitive to these sample restrictions. Specifically, we get a declining trend in joint retirement outcome across birth cohorts of the wife (from 1930-1950) which cannot be fully explained by economic factors and this result is robust to sample selection based on husband’s age, spousal age difference and work experience. To illustrate this point, I conduct sensitivity analysis to the particular set of sample restrictions. In this appendix I present actual as well as predicted labor supply transition probabilities (both unconditional and conditional on at least one spouse retiring) from the multinomial logit model for the following six alternative sample selection criteria:

1. Husband Age $\geq 55$ years, Age Difference $\leq 10$ years, Work Experience $\geq 10$ years (see Figures B.1 and B.2).

2. Husband Age $\geq 55$ years, Age Difference $\leq 20$ years, Work Experience $\geq 10$ years (see Figures B.3 and B.4).

3. Husband Age $\geq 55$ years, Age Difference $\leq 15$ years, Work Experience $\geq 5$ years (see Figures B.5 and B.6).

4. Husband Age $\geq 55$ years, Age Difference $\leq 15$ years, Work Experience $\geq 15$ years (see Figures B.7 and B.8).

5. Husband Age $\geq 51$ years, Age Difference $\leq 15$ years, Work Experience $\geq 10$ years (see Figures B.9 and B.10).

6. Husband Age $\geq 51$ years, Age Difference $\leq 10$ years, Work Experience $\geq 5$ years (see Figures B.11 and B.12).
Figure B.1: Predicted Transition Probabilities by Wife’s Birth Cohort
Figure B.2: Predicted Transition Probabilities by Wife’s Birth Cohorts, Conditional on at least One Spouse Retiring
Figure B.3: Predicted Transition Probabilities by Wife’s Birth Cohort
Figure B.4: Predicted Transition Probabilities by Wife’s Birth Cohorts, Conditional on at least One Spouse Retiring
Figure B.5: Predicted Transition Probabilities by Wife’s Birth Cohort
Figure B.6: Predicted Transition Probabilities by Wife’s Birth Cohorts, Conditional on at least One Spouse Retiring
Figure B.7: Predicted Transition Probabilities by Wife’s Birth Cohort
Figure B.8: Predicted Transition Probabilities by Wife’s Birth Cohorts, Conditional on at least One Spouse Retiring
Figure B.9: Predicted Transition Probabilities by Wife’s Birth Cohort
Figure B.10: Predicted Transition Probabilities by Wife’s Birth Cohorts, Conditional on at least One Spouse Retiring
Figure B.11: Predicted Transition Probabilities by Wife’s Birth Cohort
Figure B.12: Predicted Transition Probabilities by Wife’s Birth Cohorts, Conditional on at least One Spouse Retiring