THE PATTERNS OF PARENTAL INTERVIVOS TRANSFERS TO ADULT CHILDREN

Siqiang Yang* and Marla Ripoll†

July, 2021

Abstract

Parental intervivos transfers to adult children occur in families across the income distribution. This paper documents and analyzes novel patterns of parental intervivos transfers that are informative to dynamic models of transfers. We use longitudinal data on parental transfers from the 1996-2014 Health and Retirement Study to characterize the age profile of transfers, including the probability and the transfer amount (unconditional and conditional). We then follow the 1967-71 cohort to describe the frequency of transfers, the distribution of years between transfers, and the total transfers received during different age brackets. Last, we use a dynamic model of parental altruism to analyze the mechanisms generating the distinct transfer types observed in the data. We find that in addition to the cross-sectional patterns documented in the literature, parental altruism is essential to explain the novel dynamic facts on intervivos transfers from longitudinal data.

Key words: age profile of intervivos transfers, frequency of transfers, income profile, borrowing constraints, parental altruism

JEL Codes: D15, J12

1 Introduction

Parental intervivos transfers to adult children occur in families across the income distribution. In fact, as Gale and Scholz (1994) document, the incidence of major intervivos transfers in cross-sectional data is about 2.5 times larger than that of bequests. Understanding the patterns of parental transfers is important because they play an insurance role providing liquidity during unemployment, relieving borrowing constraints, or helping adult children purchase a home. Intervivos transfers also constitute a source of wealth accumulation.

This paper documents and analyzes novel patterns of parental intervivos transfers that are informative to dynamic models of transfers. We use longitudinal biennial data on parental transfers from the 1996-2014 Health and Retirement Study (HRS) to characterize the age profile of transfers, including the probability and the transfer amount. Since the data on parental transfers

---

*School of Economics, Nankai University. E-mail: siy10@nankai.edu.cn
†Corresponding author. Department of Economics, University of Pittsburgh. E-mail: ripoll@pitt.edu

1Using data from the 1986 Survey of Consumer Finances, Gale and Scholz (1994) document that while 9.4% of households reported giving major intervivos transfers (of at least $3,000 during 1983-1985) to non-coresident adult children, only 3.7% children received inheritances in 1986.
features many zeros, we highlight differences between the age profile of unconditional and conditional transfer amounts, providing relevant information for dynamic models. Second, we exploit the longitudinal nature of the data to follow the 1967-71 cohort over the entire period, which records the transfer they receive during ages 25-45. We use this cohort to describe the frequency of transfers, the distribution of years between transfers, and total transfers received during different age brackets. The analysis of total transfers received during ages 25-35 and 35-45 uncovers the existence of novel and distinct transfer types in longitudinal data. Last, we use a dynamic model of parental altruism to analyze the mechanisms generating the different transfer types we document. While we observe 20 years of transfer data, parents make dynamic decisions regarding transfers together with other decisions such as consumption and saving, and taking into account future periods we do not yet observe in the data. Our model implies that the income profile, the number of children and other parameters such as the level of altruism and borrowing limits, jointly determine the timing of transfers. The novel aspect of our analysis is that we use the model to understand how the different mechanisms alter the dynamic profile of transfers and translate into the different transfer types observed in panel data.

Our analysis yields three main insights. First, HRS data reveals a sharp contrast between the age profile of unconditional and conditional transfer amounts. We estimate a decreasing age profile for the probability of receiving a transfer as well as for the unconditional transfer amount received. In contrast, the transfer amount conditional on receiving does not exhibit a clear age profile, a novel finding. In fact, the decreasing age profile of unconditional transfer amount is mostly explained by the decreasing age profile of the probability of receiving. These patterns are robust to the inclusion of family and child fixed effects. More importantly, when we look at children’s age brackets, the sharpest drop in probability and transfer amount (unconditional) occurs in going from the < 30 to the 30-39 age group.\(^2\) For instance, using a simple linear estimation, the probability of receiving a transfer is 19 percentage points higher for the <30 age group, but only 7 percentage points higher for the 30-39 age group (relative to those ages 50+). The average transfer amount (in a two-year period) for these same age brackets drops from about $1,226 to $300. Notably, among those who receive positive transfers, the amount received is unrelated to the age bracket. These age profile facts are consistent with the notion that parents are more likely to transfer when children are constrained, which tends to happen when they are young, but may also happen later in life when negative shocks may run down children’s savings or when children are paying back debt.

Our second set of insights refers to the timing of transfers and transfer types we observe when we follow the 1967-71 cohort. This is the cohort for which we have enough observations to analyze the transfer patterns over the life cycle for children born around the same time, and for whom we can observe transfers as early as age 25. As for the whole sample, transfers for this cohort are infrequent: while 44% never receive transfers between ages 25-45, about 18% receive transfers once, and 10% receive twice. Three or more transfers are observed for less than 8% of the sample each. Although transfers are overall infrequent, there is substantial heterogeneity in transfer receipt among adult children in the same cohort. We also find that among those who receive, and regardless

\(^2\) Age brackets include younger than 30, 30-39, 40-49 and 50+.
of how many times they do, most receive their first transfer in 1996 when they are around age 25. In addition, for those who receive at least two transfers, most receive them two years apart. This suggests that transfers for most children in the 1967-71 cohort are concentrated during the period in which they are younger adults, confirming the age profile we document for the whole sample.3

One of the main advantages of following cohort 1967-71 is that we can construct measures of total transfers during age brackets. This analysis uncovers distinct transfer types among adult children. While 46% of children receive positive total transfers during ages 25-35, 36% receive during ages 35-45. The average total unconditional amount is $6,887 for ages 25-35 and $5,306 for ages 35-45. In contrast, the average total conditional transfer amount is almost the same across these age brackets, with those 25-35 receiving $15,032, and those ages 35-45 receiving $14,865. These patterns can be explained by the existence of different transfer types: while 20% of children in the 1967-71 cohort receive transfers only in ages 25-35 (transfer type 1), 9% receive only in ages 35-45 (transfer type 2), and 26% receive in both age brackets (transfer type 3). What is distinct about the latter group is that they receive more generously in both subperiods. A composition effect explains the lack of age profile of the conditional total transfer amount: transfer type 3 tends to increase the average of total transfers in ages 35-45. Transfer type 3 is also relatively more prevalent among parents and adult children with at least college education, and adult children with only one sibling. These correlations suggest mechanisms potentially relevant for dynamic model of transfers. We corroborate the statistical significance of these correlations using multinomial logit regressions on the transfer types. In addition, we construct a measure of total transfers for ages 25-45 and confirm that parental income, parental years of schooling and the number of siblings are significantly correlated with the probability and the total transfer amount.

The third main insight of the paper is that a dynamic model of parental altruism with credit frictions generates a rich characterization of transfer types in panel data. The model features a dynasty in which generations overlap during certain periods of the life cycle. The main prediction of the model is that parental transfers occur in the periods in which the child is most constrained, namely the periods in which the parent’s marginal benefit of transferring to the child is the largest. Three key mechanisms in the model give rise to the transfer patterns observed in longitudinal data. First, different income profiles over the life cycle, particularly differences in the slope and the peak age, give rise to the transfer types. While parental income is a known determinant of transfers in one and two-period altruistic models, the novel result here is how the specific shape of the income profile translates into different transfer types we document in HRS panel data. Given the typical parent-child age difference and the hump-shaped income profile, the income and wealth of the young adult will be lower than the parent’s. This alone raises the probability that children who are constrained would receive transfers only early in adult life (transfer type 1). But parents whose income profile is steeper and peaks later in life, might give transfers to their constrained children for more periods (transfer type 3).

The second key mechanism in the model is the number of children in the family. The presence of multiple children in the model dilutes parental resources, which tends to lower transfers to each

---

3 These parents are robust to other 5-year cohorts observed since the early 20s in the sample.
child and the probability of receiving transfers. For example, for a given income profile, a larger number of siblings may transform a transfer type 1 into a transfer type 0. In fact, even constrained children may never receive transfers (transfer type 0) when they come from families with a large number of children. The model also implies a more complicated relationship between number of children and transfers in cases where transfers across multiple generations occur. For example, when the grandparent gives to the parent and the parent gives to adult child (transfer type 3), the income profile and other parameters affect the impact of the number of children on transfers. This is the case because in making transfer decisions, the grandparent takes into account the total income of the parent and the grandchildren. Therefore, while in general more children tend to dilute parental resources, transfers across multiple generations may alter this relationship.

Last, the model provides insights into how unobserved factors may generate the transfer types observed in panel data, specifically differences in the level of altruism among parents and the borrowing limits faced by adult children. Unobserved differences in the parameter that determines parental altruism could give rise to different transfer types, even for parents with the same income profile. While it is known that more altruistic parents tend to give more, the new insight of our analysis is how the degree of altruism may change the timing of transfers and the transfer types. For example, higher level of altruism may transform a transfer type 1 into a transfer type 3. Regarding borrowing limits, we focus our analysis on young adults since credit constraints tend to bind for this group. The model predicts that for a given income profile, relaxing borrowing limits for young adults may result in parents postponing transfers for later in life (transfer type 2). In this instance parents transfer later in life to help children pay down debt. On the other hand, if saving constraints exist, as in the case of a down payment for a house, parents may increase transfers to a young adult child who is constrained.

Our paper is related to others in both the empirical and the theoretical parental transfer literature. Until recently, most of the empirical work on parental intervivos transfers was conducted using cross-sectional data. For example, Gale and Scholz (1994) use the Survey of Consumer Finances, while Altonji et al. (1997) use the Panel Study of Income Dynamics (PSID). Longitudinal data has only been used recently in few papers, including Hurd et al. (2011) and McGarry (2016), who use longitudinal biennial data from the HRS; and Scholz et al. (2014), who use data from the Wisconsin Longitudinal Study (WLS). Hurd et al.’s (2011) main focus is to characterize intervivos transfers from the perspective of parents, who are the givers. They examine the total amounts parents give in each wave to all their children together, regardless of how much each child receives and under what circumstances. Our work complements theirs by focusing on individual children and by documenting novel empirical facts of relevance to theoretical models.

McGarry’s (2016) main focus is the empirical analysis of transfers by wave, and how they are correlated with events in the life of the adult child, specifically a new divorce, a job loss, losing a home, graduating, marrying, purchasing a new home, or having new child. Our paper complements McGarry’s by focusing on other aspects of the data that are informative to dynamic models of transfers, such as the age profile, and with an emphasis on age brackets. We also examine the types of transfers observed for the 1967-71 cohort and their characteristics. Different from McGarry, we
formulate a dynamic model of parental altruism with a life cycle component, and use it to provide insights into the mechanisms explaining the data. Last, Scholz et al. (2014) use data from the WLS to analyze lifetime transfers. Due to the nature and the low frequency of the WLS data, they are not able to examine the age profile. They also do not formulate a model of parental transfers. Our paper differs from theirs on these regards.

On the theoretical side, our work is related to other models of parental transfers. An earlier literature compared the ability of models with different parental motives, such as altruism and the exchange motive, to explain features of the data. For example, Cox and Rank (1992) use a static model that combines both these motives and explore its predictions in cross-sectional data. Although our analysis does not directly test for the exchange motive, we discuss how parental altruism is necessary to explain the patterns from longitudinal data. Our model, as Cordoba and Ripoll’s (2019), is a dynamic model of parental altruism with commitment and credit constraints. Their analysis focuses exclusively on the case in which transfers to adult children are zero. While in longitudinal HRS data this is the case for roughly half of adult children, the rest do receive positive transfers. Cordoba and Ripoll (2019) do not explore the timing of parental inter vivos transfers to adult children who do receive, and they do not characterize their model to interpret the patterns observed in longitudinal data. Different from them, our analysis focuses on the timing of parental inter vivos transfers, and our model is designed to describe the variety of transfer types observed in the data.

A parallel literature on the timing of parental transfers assumes no commitment, which gives rise to strategic behavior. This is the case in Altonji et al. (1997), Brown et al. (2006, 2012), Barczyk and Kredler (2014, 2020), Boar (2020), and Chu (2020), among others. Although different in nature, our model has similar predictions to these papers, particularly regarding the role of binding borrowing constraints. Both our model and these models predict that parental transfers occur when the child faces binding credit constraints, and that this condition is necessary but not sufficient. The presence of commitment allows us to more easily consider the role of multiple siblings on parental transfers, a relevant variable in the empirical analysis. In contrast, including multiple siblings in dynamic models with no commitment generates complications, requiring additional assumptions to guarantee the uniqueness of equilibrium.

The remainder of the paper is organized as follows. Section 2 presents the empirical analysis, focusing on the age profile of transfers and the transfer patterns for the 1967-71 cohort. The analysis of this cohort suggest the existence of distinct transfer types. Section 3 describes a dynamic altruistic model of parental transfers and derives its main predictions. Numerical illustrations of the model are provided to offer insights into the different transfer types observed in the data. The section also discusses the importance of parental altruism in generating the patterns from longitudinal data. Section 4 concludes.

---

4 More recent research by Barczyk and Kredler (2020) and Chu (2020) finds that transfers may also occur when the child is not constrained, although Chu (2020) finds that 74% of the transfers occur when the child is constrained.
2 Empirical analysis

This section documents novel patterns of parental intervivos transfers to adult children in the United States. We focus on data patterns that are informative to dynamic models of parental transfers. Specifically, we explore two sets of facts: first, we take a close look at the age profile of parental transfers over the life cycle of the adult child, with particular attention to age brackets. The differential role of parental transfers by age bracket is informative to models since transfers may play a role relieving liquidity constraints early in adult life. Second, we document the patterns of transfers received by 1967-71 cohort during ages 25-45. We select this cohort because it has enough number of kid-parent pairs and it allow us to record transfers as early in adult life as possible. We focus the analysis on the frequency of transfers, the distribution of years in which the first transfer is received, and the distribution of years between transfers. We also exploit the longitudinal nature of HRS data to construct measures of total transfers received by cohort 1967-71 during different age brackets. The analysis of total transfers at ages 25-35 and 35-45 gives rise to a characterization of typical transfer types in the data. In Section 3 we use a model to interpret the correlation between transfer types and some economic and demographic characteristics.

2.1 The age profile of intervivos transfers

2.1.1 Data and summary statistics

Our main data source is the RAND biennial 1996-2014 HRS data. The HRS is a nationally representative panel survey of individuals age 50+ and spouses (regardless of age). This is the ideal longitudinal data for our purpose as it contains demographic and economic information for both parents and each of their children, as well as transfers to each child separately.

We use the largest possible sample from the HRS to estimate the age profile of intervivos transfers. Our unit of observation is a kid-parent pair over the 1996-2014 period, where we use the words kid / child to refer to the adult child. Although the HRS starts in 1992, we omit years 1992 and 1994 because the parental transfer question was different in these two years. Starting in 1996 the transfer question asks whether or not the respondent gave financial help to the child totaling $500 or more since the last wave. If financial help was provided, then the total amount given to each child is asked.

Since we would like to exploit the longitudinal nature of the HRS to estimate the age profile of transfers, we restrict our sample to the kid-parent pairs for whom transfers are reported (zero or positive) every wave. We follow McGarry (2016) and select families in which the parents do not divorce or separate during the observed period, since otherwise parents may make transfers to children with considerations different from those of intact couples. We also require that children do not coreside with parents in any wave, since under coresidency the child is implicitly receiving

\[\text{We use both the Longitudinal File and the Family Data Files.}\]
\[\text{The issue with the transfer question in 1992 and 1994 is that they ask about the amount given in the previous year only. A feature of the data is that transfers are quite infrequent, which makes it hard to properly convert one-year into 2-year amounts. In addition, the 1992 question included transfers totaling $100 or more.}\]
an unobserved transfer in the form of housing services. Finally, we select children who are age 18 or older in the first wave they are observed and who are alive in all subsequent waves.\footnote{In constructing a single kid-parent pair we define the parent as the "head" of household (either married or single). Since the HRS does not have a notion of head of household, but both spouses are called respondents, we follow the convention of the PSID and assign the male parent as "head" if both parents are present, while single parents are automatically heads regardless of gender. We retain all information concerning the spouse as part of our longitudinal record for the every kid-parent pair.}

Our sample includes 105,413 longitudinal observations representing 5,510 kid-parent pairs.\footnote{This baseline sample is reduced to 102,664 observations once we eliminate outlier observations due to clearly inconsistent reporting across waves.} Parent heads of household are on average 65 years old and 72% male. 68% of parents are married while rest are single or widowed. The mean number of children ever born is 2.85. The mean parental household income in our sample is $84,929 while mean family wealth is $535,064. Adult children are on average 40 years old, and 49% are male. 73% of them married and have on average 1.75 kids of their own. Children have 13.9 years of education (some college), and 61% of them own a home.

A salient feature of the data is that on average only 17% of children receive transfers in any given HRS wave. This statistic is consistent with findings from cross-sectional PSID data (Altonji et al. 1997 and Chu, 2000). The average transfer amount across waves is $1,085, but conditional on receiving it is $6,547 (in a 2-year period). There is a large dispersion of parental transfers: the standard deviation is $4,824 for any amount, and $10,233 conditional on receiving a positive amount. Inequality appears to be a prevalent feature of parental transfers data. Last, parental intervivos transfers over the life cycle of the adult child are quite infrequent, a feature also pointed out in McGarry (2016). While 50% of adult children never receive a positive transfer during the sample period, about 18% receive a transfer only in one wave, 10% receive in two waves, and only negligible fractions receive in more than two waves.

2.1.2 Age profile

Analyzing the age profile of intervivos transfers is of relevance for dynamic models. In particular, do parents transfer mostly to young adult children who are more likely to have liquidity constraints, to have graduated from college, to have college debt, and to be planning to purchase a home? Or do parents also give to older adult children?

In principle, it is not clear whether there is an age profile of intervivos transfers. Economists have estimated hump-shaped age profiles for labor earnings, labor supply, income and consumption. Here we will use our panel data with age, time and cohort variation to determine whether there is an age profile of intervivos transfers and what the shape of this profile may tell us about the timing of parental intervivos transfers. In deriving the age profile of transfers, we control for time effects by using year dummies, but cannot control for cohort effects since age and cohort are colinear. Tables 1 and 2 present our main results on the age profile of transfers. These tables are organized according to the empirical methods adopted: Table 1 presents the estimation using the linear statistical models for probability and transfer amounts (zero and positive), and Table 2 reports the
two-part estimation combining a logit for probability and OLS for positive transfer amounts.\textsuperscript{9}

Table 1 includes the age profile of the probability of receiving as well as the transfer amount (all observations, zero and positive). The table reports pooled OLS estimates as well as fixed effect estimates controlling for family and child fixed effects. We include year dummies in all specification in Table 1, except for the case of child fixed effects. OLS estimates show a significant effect of age on the probability and transfer amount. While we report the standard coefficient on age (top panel), we are most interested in how the probability and amount change across more detailed age brackets. We include the following age brackets: younger than 30, 30-39, 40-49 and 50+. The most interesting result is that although the probability and amount decrease across age brackets, the largest drop occurs when moving from the younger than 30 to the 30-39 bracket. In particular, the probability of receiving a transfer is 19 percentage points higher for the $<$30 age group, but only 7 percentage points higher for the 30-39 age group (age 50+ is omitted). The average (two-year) transfer amount for these same brackets drops from about $1,226 to $300.

Different from cross-sectional data, our longitudinal sample allows us to control for unobserved family and child characteristics. We find that the age profiles of the probability and transfer amount (unconditional) are robust to controlling for family and child fixed effects. As it is typical, the absolute value of the estimated coefficients is smaller in the fixed effect regressions, but the largest drop in probability and transfer amount continues to occur in going from the $<$30 to the 30-39 age bracket. For instance, as shown on the last column of Table 1, when the identification comes from observing a child over time, the average transfer amount falls from $732 for the $<$30 bracket, to $166 for ages 30-39.

Additional interesting insights on the age profile of transfers are presented in Table 2, where we implement a two-part estimation of the age profile by combining a logit model for the probability, and a OLS model for the positive transfer amounts only.\textsuperscript{10} The first two columns of Table 2 show how the logit model confirms the decreasing age profile for the probability, as well as the result that the largest drop in the odds of receiving occurs from the $<$30 to the 30-39 age group: the odds go from 3.7 to 1.8. But the OLS estimates on positive amounts show a different picture: conditional on receiving, age is not correlated with the amount and there is no clear age profile. What this finding suggests is that the decreasing age profile on transfer amounts (zero and positive) is mostly driven by the age profile of the probability of receiving: the larger fraction of zeros at older age brackets drives the average unconditional transfer amount down.

The last four columns of Table 2 present the two-part estimation with fixed effects. The conditional logit estimates for both family and child fixed effects confirm once more our findings regarding the age profile of probabilities. But regarding the positive transfer amounts, we find that once we control for family or for child fixed effects, there is no significant age profile of positive transfer amounts.

\textsuperscript{9}The age profile we report is robust to controlling for cohort effects instead of year effects. In addition, non-linear Tobit estimates confirm our results and are available upon request.

\textsuperscript{10}The two-part estimation method is also used in Scholz \textit{et al.} (2014). Relative to the linear estimation, the logit model on the probability of receiving a transfer properly takes into account the large number of zero transfers in our sample. In addition, the OLS on transfer amounts is only done on positive transfers, circumventing the issues with the zeros.
In sum, what we conclude from Tables 1 and 2 is that there is a significant decreasing age profile of the probability of receiving and the transfer amount (zero and positive), with the largest drop going from children younger than 30 to those in the 30-39 age group. This pattern is robust to a variety of estimation methods and the inclusion of family and child fixed effects. The most novel of our findings is that there is no significant age profile for positive transfer amounts: if we only look at adult children who do receive, age is not correlated with how much they receive. This result provides a testable implication for dynamic models of parental transfers. As we document next, this result also holds when we follow a specific cohort over time, namely the 1967-71 cohort.

2.2 The 1967-71 cohort

We have consistent data for a sample size of 1,141 kid-parent pairs from 846 families in the 1967-71 children’s cohort. Parents of these children are part of the Initial HRS cohort of parents (born 1931-1941). From the HRS data we can observed the transfers received by children in the 1967-71 cohort from ages 25-45. Given the age profile documented above, we select this cohort to be able to follow as many individuals a possible and to measure transfers as early as possible in adult life, when most transfers occur. The 1967-71 cohort corresponds to children in Generation X (1965-1980), which marks the beginning of the baby bust, when fertility rates started to decline in the US after the baby boom of 1946-1964 (Pew Research Center).

2.2.1 Summary statistics

This section describes the transfer patterns for the 1967-71 cohort. The left panel of Figure 1 portrays the frequency of transfers by number of waves (2-year periods) in which transfers are recorded in the HRS during 1996-2014. As shown in the figure, transfers are relatively infrequent: over a period of 20 years, 44% of adult children never receive transfers between ages 25-45, about 18% receive transfers once, and 10% receive twice. Three transfers are observed for about 8% of the sample, and larger numbers for even less. The right panel of Figure 2 reports the corresponding statistics for positive transfers only. These patterns for the 1967-71 cohort also hold for the whole HRS sample, and is consistent with what McGarry (2016) reports (Figure 1, p. 5). Panel data reveals both the overall infrequency of intervivos transfers and the heterogeneity in transfer receipt frequency among individuals from the same cohort.

Figure 2 displays the distribution of the year when those in the 1967-71 cohort receive the first transfer by frequency of transfer. As seen in the figure, even for those who receive only once during the 10 waves of the HRS, most (about 30%) receive the first transfer in 1996 when they are age 25. This figure goes up to about 50% for those who receive three times, and by construction increases

---

11The age profile results on Tables 1 and 2 are robust to the inclusion of other economic and demographic controls. While the estimated coefficients are smaller for some specifications, the patterns we obtain for age brackets remain intact. Results are available upon request.

12The transfer patterns we document in this section are robust to selecting other adjacent cohorts. Results are available upon request. Our criteria in focusing on the 1967-71 cohort involves a compromise between sample size and observing adult children as young as possible.
for those who receive more frequently. Figure 3 shows the distribution of years of distance between transfers by frequency of transfer. Even for those who receive twice, most receive transfers two years apart, namely two consecutive waves. Together, Figures 2 and 3 suggest that transfers for most children in the 1967-71 cohort are concentrated during the period in which they are younger adults, consistent with the age profile estimated above.

We further explore the transfer patterns for the 1967-1971 cohort by reporting statistics regarding the probability and total transfer amount (unconditional and conditional) by subperiod. Table 3 summarizes the results, where statistics are organized by aggregating transfers across every two waves, then every five waves, and up to all ten HRS waves. This way of presenting the statistics allows us to get a sense of both the levels of total transfers and the age profile of transfers for the 1967-71 cohort. As shown in Table 3, when we aggregate transfers every two waves into five periods, the probability of receiving transfers declines from 0.35 in period 1, down to 0.21 in period 5. The unconditional total amount declines from $3,238 in period 1 (over 4 years) to $1,666 in period 5. Both these patterns are consistent with the declining age profile of the probability and amount documented in the previous section for our whole HRS sample. Interestingly, as shown in the last column, the conditional transfer amount does not exhibit a clear age profile, just as we documented for the whole sample. These same patterns hold when we aggregate transfers every five waves into two periods. In this case, the average conditional amount children in the 1967-71 cohort receive in period 1 is $15,032 (over 10 years), while it drops slightly to $14,865 in period 2. The almost constant conditional transfer amount across these two periods is a remarkable feature of the data. Again, the unconditional average transfer amount does fall from $6,887 in period 1 to $5,306 in period 2, a fall mostly explained by the lower probability of receiving in period 2.

The last row of Table 3 reports that 56% of children in the 1967-71 cohort receive at least once during ages 25-45. The average total transfer received is $12,201, while conditional on receiving, the average total is $21,956. What these statistics show is that although in cross-sectional data transfers are not so prevalent, longitudinal data suggests that a substantial fraction of adult children receive transfers from their parents during ages 25-45.

2.2.2 Transfer types

To make progress in understanding the mechanisms generating the transfer patterns in the data, this section exploits the statistics for the two 5-wave (10 year) periods in the middle of Table 3 to characterize transfer types. Dividing the 20 years of HRS data into two 10-year periods is the minimum split that delivers a typology of transfers to capture the heterogeneity across adult children in the data. Table 4 presents the characterization of these types. Recall that period 1 corresponds to transfers received by children in the 1967-71 cohort during age bracket 25-35, and period 2 during ages 35-45. As shown at the top of Table 4, which repeats the result from Table 3, average conditional total transfers are almost identical for periods 1 and 2. But there is a heterogeneity of transfer types underlying this result. For the 1967-71 cohort we identify adult children who never receive between ages 25-45. We refer to them as transfer type 0, who represent
44% of the kid-parent pairs. Transfer type 1 corresponds to those who only receive in period 1 during ages 25-35 and represent 20% of those in the cohort. The least common is transfer type 2, who refers to adult children who only receive in period 2 during ages 35-45, and account for 9%. Last, 26% of adult children receive in both age brackets, and we refer to them as transfer type 3.

The bottom panel of Table 4 reports the average conditional total amounts by transfer type. A remarkable feature is that transfer type 3 children receive more generously in both periods, roughly twice as much on each period as the relevant type 1 and type 2 counterparts. These statistics suggest that the reason why there is no age profile for the average total conditional amount is a composition effect. In fact, both type 1 and 3 receive in period 1, with type 3 increasing the average for period-1 total transfers. In addition, both type 2 and 3 receive in period 2, with type 3 again increasing the average period-2 total transfers. In this case type 3 dominates the average, as type 2 only represent 9% of the children.

Table 5 describes the distribution of transfer types by certain observable demographic characteristics, including the average annual income of the parents, education of the parent, education of the child, and the number of siblings the child has. These are all fixed parent and child characteristics over the sample period. This table suggests some of the potential mechanisms behind the transfer types. As seen on the table, average annual parental income, which is a proxy for parental permanent income over the 20-year period sample, has large quantitative effects on the distribution of transfer types. While 65% of adult children whose parents’ household income is in the first quartile (< $40,098) are transfer type 0, only 9% are transfer type 3 on this quartile. At the other end of the distribution, 46% of adult children whose parents’ income is in the fourth quartile (> $104,972 and < $465,084) are transfer type 3, while 29% are transfer type 0. Regarding the level of education of the parent, in this case the head (male if alive), transfer type 0 is relatively more prevalent (41%) among parents who only completed high school, and significantly less prevalent for parents with at least a college degree (30%). In fact, parents with at least college tend to be more represented among transfer type 3 children.

The HRS does not report an accurate measure of the adult child’s income, since it is reported by the parent in the form of an income bracket, so for the child we only use the level of education. As seen on Table 5, children with only high school completed tend to be transfer type 0 (50%). Interestingly, type 3 children are relatively more prevalent among children with at least a college degree, implying that even highly educated children, who potentially enjoy higher income still receive parental intervivos transfers. This pattern suggests that the child’s education is not necessarily correlated with the distribution of transfer types.

The number of siblings has large quantitative effects on the composition of transfer types. While 28% of adult children with no siblings are transfer type 0, the corresponding statistic among those with three or more siblings doubles to 56%. It is also interesting to notice the difference between children who only have one sibling and those who have two. In going from one to two siblings, the representation of transfer type 0 goes from 32% to 43%, a shift that is mostly absorbed by a drop in the share of transfer type 3 from 37% to 30%. Siblings affect the distribution of transfer types in a significant way.
We complement the analysis in Table 5 with a multinomial logit regression, which is presented in Table 6. Using transfer type 0 as the base outcome, Table 6 confirms the patterns from Table 5. First, the number of sibling the child has is statistically significant in all panels: as the number of children increases, the estimated relative risk ratios show that the adult child is more likely to be a transfer type 0 than a transfer type 1 (risk ratio of 0.85), a transfer type 2 (0.82), or a transfer type 3 (0.74). Second, higher parental household income makes the adult child more likely to be a transfer type 2 (relative risk ratio of 1.05) or transfer type 3 (1.05) than a transfer type 0. Third, higher parental education makes it more likely that a child is transfer type 1, 2 or 3 than transfer type 0. Last, as suspected, higher education of the adult child is statistically significant only in making the child more likely to be transfer type 1 than transfer type 0, but there are no significant effects for other transfer types.

Tables 5 and 6 exploit the panel structure of HRS data to provide a characterization of different transfer types in the data. The correlations in these tables also suggest some of the determinants of these types. The novelty of our analysis is to determine the extent to which variables such as parental income, education of the parent and the child, and number of children in the family affect the distribution of the types that emerge from panel data. In Section 3, we deepen our understanding of these types by constructing a dynamic altruistic model of transfers. While we observe 20 years of transfer data, parents make dynamic decisions regarding transfers together with other decisions such as consumption and saving, and also taking into account periods beyond the ones we observe in the data. The model will allow us to derive additional insights on the mechanisms generating the data.

2.2.3 Total transfers

Before turning to the model, we confirm that the correlations between transfers and other variables such as parental income and siblings also hold for the total amount received by children in 1967-71 cohort. As shown in the bottom panel of Table 3, average total transfers for this cohort amount to $12,201 for the 20-year period, with an average total of $21,956 among those who receive positive amounts (56% of adult children). Table 7 reports the correlations between total transfers and some economic and demographic variables. The table reports the linear and two-part estimations. From the linear estimation on the first two columns of Table 7 we learn that parental average income and the number of siblings the child has are significantly correlated with total transfers received during ages 25-45. Parental years of schooling correlates with the probability of receiving, but not the amount (unconditional). The correlation between parental income and total transfer amount is positive, with every $10,000 of additional average annual income resulting in $747 of additional total transfers. Siblings significantly reduce total transfers: every extra sibling reduces total transfers during ages 25-45 by $1,562.

As shown on the last two columns of Table 7, similar findings hold for the two-part estimates (logit for probability and OLS for positive transfer amount). Notably, the total conditional transfer amount is increased by $896 for additional $10,000 of annual parental income. An additional sibling
reduces total conditional transfers by $1,902. The child’s years of schooling are not significant in any of the regressions, a result similar to the one found for transfer types in Table 6. In sum, the results in Table 7 confirm the statistical significance of parental income and number of child’s siblings in explaining not just the transfer types (Table 6), but also the probability and amount of total transfers for the 1967-71 cohort.

3 A model of parental transfers

This section proposes a model of parental transfers that offers insights into the possible mechanisms generating the data patterns described above, particularly the typology of transfers. Our model follows Cordoba and Ripoll (2019), but our analysis is distinct. They studied a different question and solved the model under the assumption that no adult transfers are given. But as shown above, this is the case for less than half of the adult children in HRS data. Cordoba and Ripoll (2019) did not use the model to understand parental intervivos transfer data. Our analysis solves for a version of the model that allows us to derive theoretical results and to characterize the transfer types we described above. As we show, our simple model generates a rich characterization of transfer types.

3.1 Parental problem and transfer types

Consider the case of an altruistic adult parent and his adult children in an overlapping generations setting. Adult life lasts for $T$ periods indexed by $t$. For simplicity we assume that all children are born at the same time.\footnote{Although differences in intervivos transfers have been documented among children within the same family (see for instance Scholz et al. (2014), who use the WLS), we do not have enough observations in the HRS to document these patterns. Therefore, this aspect is not a focus of our analysis.} We assume there is a gap of $F$ periods between each kid and the parent.

The parent solves the following problem

$$V(b) = \max_{[c_t; z_{t+1}; b_{t}^{F}]} \sum_{t=1}^{T} \beta^{t-1} u(c_t) + n \beta^{F} \gamma(n) V(b'),$$

subject to

$$c_t + z_{t+1} = b_t + y_t + R z_t \text{ for } 1 \leq t < F + 1$$

$$c_t + z_{t+1} + nb_t^{F} = b_t + y_t + R z_t \text{ for } F + 1 \leq t \leq T$$

$$z_{t+1} \geq z_{t+1} \text{ for } 1 \leq t < T$$

$$b_{t}^{F} \geq 0 \text{ for } F + 1 \leq t \leq T$$

where $b$ is the vector of intervivos transfers received by the parent, $\beta$ is the discount factor, $c_t$ is consumption, $n$ is the exogenous number of children, $\gamma(n)$ represents the altruistic weight per child
with $\partial \gamma(n)/\partial n < 0$ capturing diminishing marginal altruism, $n\gamma(n)$ is the total altruistic weight for all $n$ children, $b'$ is the vector of transfers the parent gives to the kid, $z_t$ are the assets in period $t$, $y_t$ is the income, $R$ is the gross interest rate, and $z_{t+1}$ is the borrowing limit. We assume $z_1 = 0$. Notice that the budget constraints in (2a) are written before and after the child is born, when the parent is age $F$. Constraint (3) implies that parental transfers cannot be non-negative. In addition, due to finite-horizon nature of the problem $z_{T+1} = 0$.

The Euler equations of this model are given by

$$u'(c_t) = \beta R_{t+1} u'(c_{t+1}) \geq \beta Ru'(c_{t+1}) \text{ for } t < T,$$  

(4)

where $R_{t+1} \geq R$ is the shadow borrowing interest rate. Notice that if the borrowing constraint does not bind, then $R_{t+1} = R$. Similarly, the optimality conditions for parental transfers to the child are given by

$$u'(c_t) \geq \gamma(n)u'(c'_{t-F}) \text{ for } F + 1 \leq t \leq T,$$  

(5)

where $c'_{t-F}$ is the consumption of the child and the inequality holds strictly when the parental transfer is zero, or $b'_{t-F} = 0$. In the equation above $u'(c_t)$ is the marginal cost to the parent of transferring to the child, while $\gamma(n)u'(c'_{t-F})$ is the marginal benefit. Notice the average altruism $\gamma(n)$ is relevant in computing the marginal benefit. Since $\gamma(n)$ is decreasing in the number of children, parents with more children have a higher discount on the marginal benefit of transferring. This feature of the model is consistent with the strong negative correlation documented between parental transfers to adult children and the number of siblings in the empirical section.

As it is apparent from optimality conditions (4) and (5), there are many possible transfer dynamics in the model. To provide insights into the transfer types characterized from HRS data we explicitly solve the model for the case in which $T = 4$ and $F = 1$. We also focus on the steady state of the model and assume that borrowing constraints are not binding after $t = 3$, or $R_4 = R$, a reasonable assumption for the later periods in adult life. To further limit the number of cases while still providing an interpretation of the data, we introduce the following assumption, which rules out the case in which parental transfers are positive in all periods, a case unlikely to hold in the data as suggested in the empirical analysis.

**Assumption 1.** $\gamma(n)\beta R < 1$

These assumptions correspond to the simplest case that still allows for a rich characterization of transfer types. The following proposition derives the key condition to determine the timing of parental transfers in the steady state of the model.

**Proposition 1.** Assume Assumption 1 holds, $T = 4$, $F = 1$ and $R_4 = R$. Then in a steady state where $c_t = c'_t$ and $b_t = b'_{t}$ for all $t$, the timing of parental transfers to the child is determined by the following conditions

$$1 \geq \gamma(n)\beta \max\{R_2, R_3\} \geq \gamma(n)\beta R_4 = \gamma(n)\beta R,$$

(6)
where $b_1 > 0$ if $1 = \gamma(n)\beta R_2$; $b_2 > 0$ if $1 = \gamma(n)\beta R_3$; and $b_1, b_2 > 0$ if $1 = \gamma(n)\beta R_2 = \gamma(n)\beta R_3$.

**Proof.** The conditions in (6) follow directly from equations (4) and (5) in a steady state with $c_t = c'_t$ and $b_t = b'_t$ for all $t$. Specifically, using (4) into (5) we have

$$u'(c_t) \geq \gamma(n)u'(c'_{t-1}) = \gamma(n)\beta R_t u'(c'_t) \geq \gamma(n)\beta R u'(c'_t) \text{ for } 2 \leq t < T,$$

and

$$u'(c_4) \geq \gamma(n)u'(c'_3) = \gamma(n)\beta R_4 u'(c'_4) = \gamma(n)\beta R u'(c'_4),$$

which in a steady state with $c_t = c'_t$ can be combined into a single expression as in (6).

The proof of Proposition 1 provides the intuition of the main mechanism at work in this model, namely that parental transfers occur in the periods in which the child is most constrained. The first inequality in (7) uses the Euler equation to transform the optimality condition for transfers in the steady state into $1 \geq \gamma(n)\beta R_t$. In this case, if the inequality is strict, then $b_{t-1} = 0$. The second inequality in (7) reduces to $R_t \geq R$, which holds with strict inequality when the borrowing constraint binds in period $t-1$. Equation (6) implies that if for instance $1 = \gamma(n)\beta R_2 > \gamma(n)\beta R_3 > \gamma(n)\beta R_4 = \gamma(n)\beta R$, then all parental transfers would be zero except $b_1 > 0$. The reason is that although in this case the borrowing constraint for the child binds in periods $t = 1$ and $t = 2$, the marginal benefit of the parental transfer is largest in $t = 1$. Alternatively, if for instance $1 = \gamma(n)\beta R_2 = \gamma(n)\beta R_3 > \gamma(n)\beta R_4 = \gamma(n)\beta R$, then the borrowing constraint still binds in periods $t = 1$ and $t = 2$, but now both $b_1 > 0$ and $b_2 > 0$ since the marginal benefit of the transfer is largest in both periods.

Notice that under Assumption 1, the case in which equation (6) reads $1 = \gamma(n)\beta R_2 = \gamma(n)\beta R_3 = \gamma(n)\beta R_4 = \gamma(n)\beta R$ is precluded, so it is not possible to have positive transfers in every period, or $b_t > 0$ for $2 \leq t < T$. Assumption 1 allows us to focus on the model’s predictions on $b_1$ and $b_2$. The following proposition characterizes the transfer patterns predicted by the model, which parallel the ones documented in HRS data.

**Proposition 2.** Assume Assumption 1 holds, $T = 4$, $F = 1$ and $R_4 = R$. Then in a steady state where $c_t = c'_t$ and $b_t = b'_t$ for all $t$, the following types of parental transfers may occur:

**Transfer type 0** - the adult child never receives a positive transfer or

$$b_1 = b_2 = b_3 = 0,$$

which occurs when either of the following conditions hold

$$1 > \gamma(n)\beta R_2 = \gamma(n)\beta R_3 = \gamma(n)\beta R_4 = \gamma(n)\beta R,$$

(9)

$$1 > \gamma(n)\beta R_2 > \gamma(n)\beta R_3 = \gamma(n)\beta R_4 = \gamma(n)\beta R,$$

(10)
1 > (n)βR_3 > (n)βR_2 = (n)βR_4 = (n)βR, \tag{11}
1 > (n)βR_2, (n)βR_3 > (n)βR_4 = (n)βR. \tag{12}

Transfer type 1 - the child receives positive transfers only in period \( t = 1 \) or

\[ b_1 > 0, \text{ and } b_2 = b_3 = 0, \]

which occurs when either of the following conditions hold

\[ 1 = (n)βR_2 > (n)βR_3 = (n)βR_4 = (n)βR, \tag{13} \]
\[ 1 = (n)βR_2 > (n)βR_3 > (n)βR_4 = (n)βR. \tag{14} \]

Transfer type 2 - the child receives positive transfers only in period \( t = 2 \) or

\[ b_2 > 0, \text{ and } b_1 = b_3 = 0, \]

which occurs when either of the following conditions hold

\[ 1 = (n)βR_3 > (n)βR_2 = (n)βR_4 = (n)βR, \tag{15} \]
\[ 1 = (n)βR_3 > (n)βR_2 > (n)βR_4 = (n)βR. \tag{16} \]

Transfer type 3 - the child receives positive transfers in periods \( t = 1, 2 \) or

\[ b_1 > 0, \; b_2 > 0, \text{ and } b_3 = 0, \]

which occurs when either of the following condition holds

\[ 1 = (n)βR_2 = (n)βR_3 > (n)βR_4 = (n)βR. \tag{17} \]

Proof. All conditions follow from the inequalities in (6).

Proposition 2 shows that our model delivers a unique profile of parental transfers in the steady state as long as the credit constraint is binding at least once over the life cycle.\textsuperscript{14} The proposition

\textsuperscript{14}Outside of the steady state the pattern of parental transfers may be indeterminate in our model. However, by
also reinforces the idea that adult children may face binding credit constraints during some periods, yet they might not receive transfers. If they receive a transfer, it will only happen in a period in which they are most constrained in their lifetime. Take for example transfer type 1, which occurs under either of the conditions (13) or (14). In (14), the adult child is constrained in periods $t = 1$ and $t = 2$, yet the child only receives period-1 transfers because that is the period when the constraint is tightest.

Another insight from Proposition 2 is that parents may delay transfers, as it is the case for transfer type 2 under condition (16). In this case the child is constrained in periods $t = 1$ and $2$, but the parent delays the transfer for period $t = 2$ because that is when the child is most constrained.

The mechanism at work here is that a child might be constrained, but if the parental marginal cost of the transfer is larger than the marginal benefit the parent receives, no transfer occurs. In other words, being constrained is a necessary condition for a transfer to occur, but it is not sufficient. Notice also the role played by the altruistic weight $\gamma(n)$ in equations (9) through (17). Everything else equal, the lower $\gamma(n)$ is, the higher the chances that the child will receive no transfers as an adult. A similar role applies to discount factor $\beta$ and the interest rate $R$. In this respect the model predicts that even if a child is constrained, a transfer may not occur if either the altruistic weight $\gamma(n)$, the discount factor $\beta$ or the interest rate $R$ are too low.

Notice that the shadow interest rate $R_t$ is endogenous and it is given by the marginal rate of substitution or

$$R_{t+1} = \frac{u'(c_t)}{\beta u'(c_{t+1})},$$

which in turn depends on the income profile $\{y_t\}_{t=1}^T$ and the borrowing limits $\{z_{t+1}\}_{t=1}^3$. Therefore, which of the transfer types in Proposition 2 occurs depends on the income profile, the borrowing limits and the number of children. Next section explores these mechanisms in model detail. Finally, notice the overlapping generations structure of the model implies that parents may also receive intervivos transfers from their own parents. Therefore we could have a child receiving a transfer from the parent in period $t = 1$, together with a parent receiving a transfer from his/her own parent (child’s grandparent) receiving a transfer in period $t = 2$.

### 3.2 Mechanisms

In this section we exploit the closed-form solutions of the model to provide insights into the main mechanisms of the model, namely the income profile, borrowing limits, and number of siblings. Proposition 3 summarizes some comparative statics for specific functional forms for utility and child discounting.

**Proposition 3.** Assume Assumption 1 holds, $T = 4$, $F = 1$ and $R_4 = R$. Assume also $u(c) = \log(c)$ and $\gamma(n) = n^{-\varepsilon}$. Then in a steady state where $c_t = c'_t$ and $b_t = b'_t$ for all $t$, the following focusing on the unique steady-state predictions, our model provides insights into the mechanisms generating the transfer types in the data.
comparative static results hold:

**Income profile** - for transfer types 1 and 3,

\[
\frac{\partial b_1}{\partial y_1} < 0, \quad \frac{\partial b_1}{\partial y_2} > 0, \quad \frac{\partial b_1}{\partial y_3} \geq 0, \quad \frac{\partial b_1}{\partial y_4} \geq 0,
\]

and for transfer types 2 and 3,

\[
\frac{\partial b_2}{\partial y_1} \leq 0, \quad \frac{\partial b_2}{\partial y_2} < 0, \quad \frac{\partial b_2}{\partial y_3} > 0, \quad \text{and} \quad \frac{\partial b_2}{\partial y_4} > 0.
\]

**Borrowing limits** - for transfer type 1,

\[
\frac{\partial b_1}{\partial z_2} > 0, \quad \frac{\partial b_1}{\partial z_3} \leq 0,
\]

for transfer type 2,

\[
\frac{\partial b_2}{\partial z_2} \leq 0, \quad \frac{\partial b_2}{\partial z_3} > 0,
\]

and for transfer type 3,

\[
\frac{\partial b_1}{\partial z_2} > 0, \quad \frac{\partial b_2}{\partial z_3} > 0
\]

if \( n > R \) then \( \frac{\partial b_1}{\partial z_3} < 0 \) and \( \frac{\partial b_2}{\partial z_2} > 0 \).

**Number of children** - for transfer types 1 and 2,

\[
\frac{\partial b_1}{\partial n} < 0 \quad \text{and} \quad \frac{\partial b_2}{\partial n} < 0.
\]

**Proof.** See Appendix.

Several insights emerge from Proposition 3. First, the entire income profile affects the transfer amounts. For instance, higher \( y_1 \) decreases \( b_1 \). In this case, a higher \( y_1 \) makes the typical income profile flatter, since \( y_2/y_1 \) decreases. Because there is a one-period age difference between the parent and the child, a lower \( y_2/y_1 \) reduces the income difference between them, resulting in lower parental transfers. In addition, higher \( y_1 \) may also decrease \( b_2 \). This is the case because higher resources in period \( t = 1 \) may increase the child’s saving, resulting in lower transfers in period \( t = 2 \) (transfer type 2 under condition 15). However, if the child is constrained in period \( t = 1 \) but does not receive a transfer (\( b_1 = 0 \)), higher \( y_1 \) does not affect \( b_2 \) when the borrowing constraint is the tightest in period \( t = 2 \) (transfer type 2 under condition 16). In this case the child is hand-to-mouth in period \( t = 1 \), so that higher income only matters for consumption \( c_1 \).
Next, a higher $y_2$ decreases $b_2$. The more resources the child has in a given period, the less transfer amount the child receives in that period. On the other hand, a higher $y_2$ increases $b_1$. In this case, the steeper income profile $y_2/y_1$ results in the parent having higher income than the child, who is constrained in period $t = 1$ and will receive higher transfers. Regarding future resources, we find that higher future income $y_3$ and $y_4$ may increase $b_1$. Specifically, this occurs if the borrowing constraint only binds in period $t = 1$, case in which future resources can also be used in equalizing marginal utilities across generations. If the constraint also binds $t = 2$, but no transfers are given because the constraint is tightest in $t = 1$ (transfer type 1 under condition 14), then future resources cannot be used for intergenerational consumption smoothing and they do not affect transfer $b_1$. Last, the higher $y_3$ or $y_4$ are, the higher period-2 transfers $b_2$. This is the case because being constrained in $t = 2$ is necessary to receive a transfer in these ages. Since by assumption the borrowing constraint does not bind in $t = 3$, resources received then help provide transfers to constrained children in period $t = 2$ (transfer types 2 and 3). We numerically illustrate these mechanisms below by comparing the effect of different income profiles on the transfer types.

Second, borrowing limits also affect transfer amounts. Here we only discuss the case of relaxing the borrowing limits in $t = 1$, since younger adults are more likely to be constrained. Decreasing $z_2$, or relaxing the borrowing limit in $t = 1$, results in lower period-1 transfers $b_1$ for transfer types 1 and 3. In these cases, if the child has more access to credit in period $t = 1$, then the parent transfers less. Having more access to credit in $t = 1$ (lower $z_2$) also affects period-2 transfers $b_2$. This only occurs if $z_2$ binds, which corresponds to transfer type 2 under condition (16), or for transfer type 3. In the former case, the child acquires more debt in $t = 1$, and the parent transfers more in $t = 2$ to help the child pay back the debt. Results are more subtle for the case of transfer type 3, when the child acquires more debt in $t = 1$, but receives transfers both in $t = 1$ and $t = 2$. It turns out that for transfer type 3, if $n > R$, then having more access to credit in $t = 1$ results in lower period-2 transfers $b_2$. The intuition for this result can be traced to the fact that for transfer type 3, simultaneous transfers occur from the grandparent to the parent, and from the parent to the child. The following equation, which is derived in the Appendix as part of the proof of Proposition 3, helps explain this mechanism. For transfer type 3, $b_2$ is given by

$$b_2 = \frac{n\gamma(n) + (n\gamma(n))^2}{1 + n\gamma(n) + (n\gamma(n))^2 + \beta n} \left[ \frac{y_3 + Rz_3 + \frac{1}{R}y_4}{\text{grandparent resources}} \right] - \frac{1 + \beta}{1 + n\gamma(n) + (n\gamma(n))^2 + \beta n} \left[ \frac{y_1 - z_2}{\text{child resources}} + \frac{y_2 + Rz_2 - z_3}{\text{parent resources}} \right].$$

In the case of transfer type 3, we can think of $b_2$ as the transfer the grandparent gives to the parent, which occurs at the same time the parent is giving $b_1$ to each of his children. The grandparent is living through period $t = 3$, the parent is in the second period of life $t = 2$, and the child is a young adult ($t = 1$). In making a decision on $b_2$, the grandparent takes into account his own income, as well as the income of his children and grandchildren. The first term on the right-hand-side of the
The equation above involves the resources the grandparent has, which include his income $y_3$, his assets $R_{23}$, and the present value of his future income $y_4/R$ (the borrowing constraint does not bind for the grandparent). Since in the steady state the grandparent has $n$ children, these resources are diluted through term $1/n$. Notice that $b_2$ is increasing in the resources of the grandparent. Now, the second term of the equation above involves the resources of the parent and his $n$ children. The former includes income $y_2$ and net assets $R_{22} - R_{32}$, while the latter corresponds to income net of saving $y_1 - z_2$. Notice that $b_2$ is decreasing in total resources of the parent plus his $n$ children. More importantly, if $n > R$, decreasing $z_2$, or relaxing the borrowing limit in $t = 1$, results in lower $b_2$. This is the case because the $n$ children in $t = 1$ have now more resources, while the parent has less resources because he has to pay more debt at rate $R$. But since $n > R$, then total children plus parent resources are higher, resulting in the grandparent transferring less $b_2$ to the parent. In other words, in deciding $b_2$ the grandparent takes into account that his child will now transfer less to his grandchildren, since the latter can borrow more.

Last, regarding the number of children, we find that larger $n$ reduces period-1 transfers $b_1$ for transfer type 1, and period-2 transfers $b_2$ for transfer type 2. Both of these work through $n$ diluting parental resources in the budget constraint. Although a larger $n$ also increases the total weight of children’s utility in the parent’s utility, the diluting effect of $n$ dominates. For transfer type 3 larger $n$ results in lower transfers, but only under certain conditions, which are not included in Proposition 3 because they are complicated and not easy to interpret (see Appendix). These conditions also involve the dilution effect of $n$ and the higher total altruistic weight for larger $n$, although for transfer type 3 we again have simultaneous transfers from grandparents to parents, and parents to children.

### 3.3 Numerical illustration

While Proposition 3 provides theoretical results on comparative statics for a given transfer type, it is harder to derive analytical results on the specific income profiles that generate each transfer type, and also on how for a given income profile, changes in specific model parameters may result in switches across transfer types. In this section we present some numerical illustrations to analyze these cases. Our model is not suitable for calibration purposes because in addition to being stylized, we do not have enough information on the income profile in the HRS to compute the relevant moments. However, our model provides us with an understanding of the mechanisms necessary to replicate the empirical patterns documented in Section 2.

#### 3.3.1 Income profile

Figure 4 portrays examples of the income profile that generate the different transfer types in Proposition 2. To generate Figure 4 we set all borrowing limits to zero, or $z_2 = z_3 = z_4 = 0$. We also set $n = 2$, assume an annual interest rate of 3%, and $\beta = 0.442$. As in Proposition 3,

---

15 Recall that under transfer type 3 the borrowing constraint binds in $t = 1$ (child) and $t = 2$ (parent).

16 This numerical simulation assumes a length of period of 20 years.
we assume \( u(c) = \log(c) \) and \( \gamma(n) = \gamma n^{-\varepsilon} \), and set \( \varepsilon = 0.2 \) and \( \gamma = 0.7 \). The income profile and transfer amounts displayed in Figure 4 are relative to \( y_1 \), which is the total income during the first period of adult life.

The top panel in Figure 4 displays income profiles that generate the different transfer types. The income profile corresponding to transfer type 3 is distinct in that the income profile is the steepest and the peak occurs later. As shown in the bottom panel of Figure 4, this increasing income profile allows parents to transfer to their adult children both in periods 1 and 2 (\( b_1 > 0 \) and \( b_2 > 0 \)). These parents not only give to their adult children in both periods, but they also give them larger amounts. Although we do not have the full income profile of parents in the HRS, we verified using PSID data that steep income profiles peaking later in life do exist, typically among college graduates. While there is no longitudinal transfer data in the PSID, recall from Table 5 that parents with at least college and/or higher levels of income tend to be more represented among transfer type 3 in the HRS.

The importance of the income profile can be again seen by noticing the case of transfer type 0. As seen in the top panel of Figure 4, when the income profile is almost flat between periods 1 and 2, parents do not transfer at all. In this case, since the age difference between the parent and the child is one period and the income of the child is similar to that of the parent, the marginal cost of transferring is higher than the marginal benefit to the parent. Flatter income profiles are more typical among those with less than a college education in the PSID. Regarding the income profile corresponding to the transfer type 1, notice that it is not as steep as the transfer type 3 case, but initially steeper than the income generating transfer type 0. As shown in the bottom panel, the transfer amount for transfer type 1 is lower than for transfer type 3 in period \( t = 1 \).

Last, the income profile that generates transfer type 2 is distinct in that income slightly drops between periods \( t = 1 \) and \( t = 2 \). In this case borrowing constraints are most binding in period \( t = 2 \) and the adult child receives a transfer then. This income profile is not as common, but it does exist in PSID data. It is then reasonable that transfer type 2 is the least typical in HRS data as reported in Table 4 (9% of adult children). In sum, the income profiles displayed in Figure 4 provide additional details into the specific shapes that generate the different transfer types. Although the theoretical results we derive come from a stylized model, the insights the model offers on the importance of the income profile are intuitive and the income profiles are realistic.

### 3.3.2 Altruism

The top-left panel of Figure 5 illustrates the effect of changing the level of altruism parameter \( \gamma \) on transfers. Although it might be obvious that increasing \( \gamma \) results in higher transfers, the novelty of this analysis is how the changes in \( \gamma \) may generate switches across the transfer types observed in longitudinal data. Taken as given the income profile from Figure 4 that generates transfer type 1, Figure 5 shows that starting with the baseline value \( \gamma = 0.7 \), increasing it to \( \gamma = 0.95 \) switches the transfer type from 1 to 3. Higher altruism then results in not only higher transfer amounts, but in transfers over more periods. In contrast, decreasing altruism to \( \gamma = 0.65 \) switches the transfer
type from 1 to 0. We conclude that unobserved heterogeneity in the degree of parental altruism generates various transfer types for parents with identical income profiles.

3.3.3 Number of children

The top-right panel of Figure 5 illustrates the effect of changes in the number of children \( n \) on transfers. The benchmark from Figure 4 corresponds to the income income profile generating transfer type 1 with \( n = 2 \). As seen in Figure 5, for the same income profile, an increase in the number of children to \( n = 3 \), switches the transfer type from 1 to 0. On the other hand, decreasing the number of children to \( n = 1 \) does not generate a change in the transfer type, but results in significantly higher transfers in period 1. These numerical illustrations echo the facts documented in Table 5 on how the number of siblings matters for the distribution of transfer types for the 1967-71 cohort.

3.3.4 Borrowing limits in period 1

From Proposition 3 we learn that relaxing period-1 borrowing limits results in lower transfer amount \( b_1 \) for transfer type 1 and higher transfer amount \( b_2 \) for transfer type 2. The bottom-left panel of Figure 5 illustrates the income profile that generates transfer type 1 under the assumption that \( z_2 = 0 \) may result in a different transfer type when borrowing limit \( z_2 \) is changed. First, if some borrowing is allowed, in particular if young adults in period 1 are allowed to borrow up to 40% of their income, or \( z_2 = -0.4 \times y_1 \), there is a switch from transfer type 1 to 2. In this case the parent postpones the transfer to period 2 to help the child pay down the debt. This example illustrates how parents may serve as substitutes of missing credit markets for their young adult children. Next, if saving constraints are present, there is no switch away from transfer type 1, but transfer amount \( b_1 \) increases significantly. An example of a saving constraint is a down payment for a new home. In Figure 5 we consider the case of \( z_2 = 0.1 \times y_1 \) so that the down payment corresponds to 10% of period-1 income. The model captures well the case in which even for the same income profile, children may receive larger period-1 transfers if they need to save in order to purchase a home and the saving constraint is binding.

3.3.5 Parent-child age difference

So far we have only considered the case in which the age difference between the child and the parent is one period, or \( F = 1 \). It can be shown that when \( F = 2 \) and \( T = 4 \) the key condition in (6) summarizing the timing of parental transfers in Proposition 1 becomes

\[
1 \geq \gamma(n) \beta^2 \max\{\prod_{s=2}^{3} R_s, \prod_{s=3}^{4} R_s\} \geq \gamma(n)(R \beta)^2,
\]

where the shadow interest rates are now compounded due to the longer age difference between the parent and the child. Although the characterization of the solution in this case is more involved,
the bottom-right panel of Figure 5 illustrates the solution numerically.\textsuperscript{17} Again the panel continues to consider the income profile generating transfer type 1 in Figure 4, as well as all other parameter values. As shown in Figure 5, when the parent-child age difference increases from $F = 1$ to $F = 2$, there is no switch on the transfer type, but the period-1 transfer $b_1$ is larger. For this particular income profile, the older parent has both higher income and wealth than the adult child, resulting in a larger transfer amount.

### 3.4 The role of parental altruism

Our model of parental altruism generates a rich set of predictions that can explain the types of transfers observed in the data. As we now discuss, relative to other transfer motives considered in the literature, altruism is essential to rationalize the patterns from longitudinal data. An earlier literature compared the ability of the altruism and exchange motives to explain the data. For example, Cox and Rank (1992) used a static model combining both these motives, but due to limited data, the predictions were only compared in a cross section. Our model and the novel patterns we document provide us with an opportunity of revisiting the comparison of different motives in the context of panel data.

Cox and Rank (1992) combine the exchange and altruistic model by posing a parental utility function of the form $V_p = V(c_p, s, U(c_k, s))$, where $V_p$ is the utility of the parent, $c_p$ is parental consumption, $s$ is the service the child offers the parent, $U(\cdot)$ is the utility of the child, and $c_k$ is the child’s consumption. Altruism is present in this formulation because the parent cares about the utility of the child, and the exchange motive is captured by the child’s provision of a service to the parent (companionship, visits). Under the assumption that $\partial U/\partial s < 0$, as the income of the child increases, the parent would need to transfer a higher amount to the child for them to offer the service, which depending on the demand elasticity from the parent’s side, it could result in less services being provided.

One of the key features we document from HRS panel data is the low frequency of transfers over time. Our altruistic model is consistent with this pattern because transfers are observed only when the child is most constrained to borrow. For the exchange motive to be consistent with this pattern, the demand for services would need to be infrequent, but it is not clear why that would be the case. If anything, one may expect the demand for services to increase as the parent ages, but as we also document from the HRS, transfers tend to be concentrated when the child is a young adult. The predominance of binding borrowing constraints early in life tends to favor the altruistic motive. Cox and Rank (1992) argue that the exchange motive could still act through liquidity constraints, as that parents may pay in advance for a service they expect the child to provide when the parent is older. But even if this was true, other patterns from panel data tend to favor the altruistic model.

For example, another salient feature we document from HRS data is that while the probability

\textsuperscript{17}When $F = 2$ and $T = 4$, there are some solutions for which the consumption profile is unique but there are multiple configurations for the timing of transfers. In Figure 5 we restrict the comparison for the case of transfer types for which the solution is unique.
and the unconditional transfer amount decrease with age, there is no age profile for the conditional transfer amount. Our altruistic model explains this feature of the data through the composition effect generated by the different transfer types we document in the data. In particular, the presence of children who are transfer type 3, who receive both earlier and later in life and more generously, is key in raising the average conditional amount of later adult years. Getting no age profile for the conditional transfer amount would be harder in the exchange model because with an income profile typically increasing until late in life, the price of the service the child provides would increase over time. From this perspective, there would necessarily be some age profile attached to conditional transfer amounts associated with the exchange motive. While we cannot rule out the existence of the exchange motive, we can conclude that parental altruism is an important feature for a model of parental transfers to be consistent with the facts from longitudinal data.

Other recent papers in the literature have also emphasized the rich set of predictions generated by the altruistic model (Barczyk and Kredler, 2020; and Chu, 2020). Although earlier work by Altonji et al. (1997) had rejected the altruism hypothesis, these recent papers cast a doubt on this rejection and provide renewed support to parental altruistic models. These papers also show that the altruistic model can match many features of PSID cross-sectional data on parental transfers (Chu, 2020). We complement these recent papers by bringing attention to the ability of altruistic models to also explain features of parental intervivos transfers from panel data. In addition, we expand the analysis by explicitly incorporating the number of children and the its role in affecting the probability and the amount of parental transfers.

4 Concluding comments

This paper contributes to the literature of parental intervivos transfers by documenting new facts using HRS panel data. Two salient empirical patterns emerge. First, since the data on parental transfers features many zeros, we find that the decreasing age profile of transfer amounts is mostly driven by the decreasing age profile of the probability of receiving a transfer. But conditional on receiving, there is no age profile for transfer amounts. These findings hold both for transfers by wave and for total transfers received during different age brackets. Given the infrequent nature of transfers, these patterns are not obvious.

Second, following the 1967-71 cohort we find that most children receive their first transfer at age 25, and that the most common distance between transfers is two years. In addition, computing total transfers by age brackets 25-35 and 35-45, we find that while 44% of adult children never receive (transfer type 0), 20% only receive in ages 25-35 (type 1), 9% only receive in ages 35-45 (type 2), and the remaining 26% receives in both periods and more generously (type 3). We find that the rich transfer types we document are correlated with parental income, parental education and number of children.

The facts we document are interpreted through the lenses of a dynamic model of parental altruism, where the income profile over the life cycle, the level of parental altruism, the number of children in the family and borrowing limits play key roles generating the patterns observed in
the data. The novelty of the analysis is to provide insights into how these mechanisms generate switches across transfer types in panel data. For instance, changing the shape and the peak of the income profile alters the timing of transfers and the transfer types. In addition, for a given income profile, unobserved heterogeneity in the level of parental altruism and borrowing limits faced by young adult children, can also generate different transfer types. We conclude that our model contributes to the analysis of longitudinal parental transfer data by providing details on the specific mechanisms behind the distribution of transfer types we document.

Our analysis is limited by data availability. First, although HRS data is perhaps the best longitudinal data we have on parental transfers, other economic variables are limited within the HRS. Notably, the full income profile of the parent is not observed in the HRS, and the data on the income of the adult child is only measured in intervals, with quite limited sample coverage. In contrast, the PSID has good data on individuals’ income profile over time, but parental transfer data is only available in two cross-sectional modules. Given the infrequent nature of transfers, the cross-sectional transfer patterns from the PSID are limited. Second, complete data on transfers received by multiple children from the same family over time is also limited in the HRS. This prevents us from using HRS data to study differential transfers across children over time. Although the altruistic model provides clear predictions on transfer differentials among children, we are not able to see how these evolve over time in the data for a good enough sample of children. Last, there is not yet a HRS sample to follow individuals from early adulthood all the way into the age when they may receive bequests. While we were able to measure total transfers in ages 25-45 for the 1967-71 cohort, we do not yet have data to study bequests for this cohort. This additional data would inform the relative role intervivos transfers and bequests play as two major components of intergenerational transfers. We leave this question for future research.

References


APPENDIX - PROOF OF PROPOSITION 3

The proof of Proposition 3 requires solving the steady state of the model for the case of log utility, 
\( u(c) = \log(c) \), and child discounting \( \gamma(n) = n^{-\varepsilon} \), and analyzing separately all the transfer types with positive transfers from Proposition 2.

TRANSFER TYPE 1 under condition (13) - In this case the borrowing constraint binds in period 1 only and transfers are only received in period 1, or 

\[
\begin{align*}
  b_1 &> 0, b_2 = b_3 = 0, \\
  R_2 &> R_3 = R_4 = R, \\
  z_2 &= \hat{z}_2, z_3 > \hat{z}_3, \text{ and } z_4 > \hat{z}_4.
\end{align*}
\]

Equations (4) and (5) together with the budget constraints imply the following steady state solution,

\[
\begin{align*}
  c_1 &= \frac{n\gamma(n)}{1 + n\gamma(n) + \beta + \beta^2} \left[ y_1 - \hat{z}_2 + \frac{1}{n} \left( y_2 + R\hat{z}_2 + \frac{y_3}{R} + \frac{y_4}{R^2} \right) \right], \\
  c_2 &= \frac{1}{\gamma(n)} c_1, \\
  c_3 &= \beta R c_2 = \frac{\beta R}{\gamma(n)} c_1, \\
  c_4 &= (\beta R)^2 c_2 = \frac{(\beta R)^2}{\gamma(n)} c_1, \\
  b_1 &= \frac{n\gamma(n)}{1 + n\gamma(n) + \beta + \beta^2} \frac{1}{n} \left[ y_2 + R\hat{z}_2 + \frac{y_3}{R} + \frac{y_4}{R^2} \right] - \frac{1 + \beta + \beta^2}{1 + n\gamma(n) + \beta + \beta^2} \left[ y_1 - \hat{z}_2 \right], \\
  z_3 &= \frac{\beta + \beta^2}{1 + \beta + \beta^2} \left[ y_2 + R\hat{z}_2 - nb_1 \right] - \frac{1}{1 + \beta + \beta^2} \left[ \frac{y_3}{R} + \frac{y_4}{R^2} \right], \\
  z_4 &= \frac{c_4 - y_4}{R}.
\end{align*}
\]

The comparative statics for income ratios in Proposition 1 are then given by

\[
\begin{align*}
  \frac{\partial b_1}{\partial y_1} &= -\frac{1 + \beta + \beta^2}{1 + n\gamma(n) + \beta + \beta^2} < 0, \\
  \frac{\partial b_1}{\partial y_2} &= \frac{\gamma(n)}{1 + n\gamma(n) + \beta + \beta^2} > 0, \\
  \frac{\partial b_1}{\partial y_3} &= \frac{n\gamma(n)}{1 + n\gamma(n) + \beta + \beta^2} \frac{1}{n R} > 0.
\end{align*}
\]
and
\[ \frac{\partial b_1}{\partial y_4} = \frac{n \gamma(n)}{1 + n \gamma(n) + \beta + \beta^2 n R^2} > 0. \]

For the case of borrowing limit \( z_2 \) we have
\[ \frac{\partial b_1}{\partial z_2} = \frac{\gamma(n) R + 1 + \beta + \beta^2}{1 + n \gamma(n) + \beta + \beta^2} > 0. \]

Finally, for number of kids the comparative statics are given by
\[ \frac{\partial b_1}{\partial n} = \frac{\gamma'(n)(1 + \beta + \beta^2) - \gamma(n)^2}{(1 + n \gamma(n) + \beta + \beta^2)^2} \left[ y_2 + R z_2 + \frac{y_3}{R} + \frac{y_4}{R^2} \right] \]
\[ + \frac{(1 + \beta + \beta^2)(\gamma(n) + n \gamma'(n))}{(1 + n \gamma(n) + \beta + \beta^2)^2} [y_1 - z_2] < 0, \]

where it can be shown that the expression above is negative because \( b_1 > 0, \gamma(n) + n \gamma'(n) = \gamma(1 - \varepsilon)n^{-\varepsilon} > 0 \) and \( \gamma'(n) < 0. \)

**TRANSFER TYPE 1 under condition (14)** - In this case the borrowing constraint binds in periods 1 and 2, but transfers to the child only occur in period 1, or

\[ b_1 > 0, b_2 = b_3 = 0, \]
\[ R_2 > R_3 > R_4 = R, \]
\[ z_2 = \bar{z}_2, \ z_3 = \bar{z}_3, \ and \ z_4 > \bar{z}_4. \]

Equations (4) and (5) together with the budget constraints imply the following steady state solution,

\[ c_1 = \frac{n \gamma(n)}{1 + n \gamma(n)} \left[ y_1 - \bar{z}_2 + \frac{1}{n} (y_2 + R \bar{z}_2 - \bar{z}_3) \right], \]
\[ c_2 = \frac{1}{\gamma(n)} c_1, \]
\[ c_3 = y_3 + R \bar{z}_3 - z_4 = \frac{1}{1 + \beta} \left[y_3 + R \bar{z}_3 + \frac{y_4}{R}\right], \]
\[ c_4 = \beta R c_3, \]
\[ b_1 = \frac{n \gamma(n)}{1 + n \gamma(n)} \frac{1}{n} \left[y_2 + R \bar{z}_2 - \bar{z}_3\right] - \frac{1}{1 + n \gamma(n)} \frac{1}{y_1 - \bar{z}_2}, \]

\[ z_4 = \frac{\beta}{1 + \beta} \left[y_3 + R \bar{z}_3\right] - \frac{1}{1 + \beta} \frac{y_4}{R}. \]
The comparative statics for income ratios in Proposition are given by

\[
\frac{\partial b_1}{\partial y_1} = -\frac{1}{1 + n\gamma(n)} < 0
\]

\[
\frac{\partial b_1}{\partial y_2} = \frac{\gamma(n)}{1 + n\gamma(n)} > 0,
\]

and

\[
\frac{\partial b_1}{\partial y_3} = \frac{\partial b_1}{\partial y_4} = 0.
\]

For the case of borrowing limits \(\bar{z}_2\) and \(\bar{z}_3\) we have

\[
\frac{\partial b_1}{\partial \bar{z}_2} = \frac{\gamma(n)R + 1}{1 + n\gamma(n)} > 0,
\]

and

\[
\frac{\partial b_1}{\partial \bar{z}_3} = -\frac{\gamma(n)}{1 + n\gamma(n)} < 0.
\]

Finally, for number of kids the comparative statics are given by

\[
\frac{\partial b_1}{\partial n} = \frac{\gamma'(n) - \gamma(n)^2}{(1 + n\gamma(n))^2} [y_2 + R\bar{z}_2 - \bar{z}_3] + \frac{\gamma(n) + n\gamma'(n)}{(1 + n\gamma(n))^2} [y_1 - \bar{z}_2] < 0,
\]

where it can be shown that the expression above is negative because \(b_1 > 0\), \(\gamma(n) + n\gamma'(n) = \gamma(1 - \varepsilon)n^{-\varepsilon} > 0\) and \(\gamma'(n) < 0\).

**TRANSFER TYPE 2 under condition (15)** - In this case, the borrowing constraint binds in period 2 only and transfers are only received in period 2, or

\[
b_2 > 0, b_1 = b_3 = 0,
\]

\[
R_3 > R_2 = R_4 = R,
\]

\[
z_3 = \bar{z}_3, \ z_2 > \bar{z}_2, \text{ and } z_4 > \bar{z}_4.
\]

Equations (4) and (5) together with the budget constraints imply the following steady state solution,

\[
c_1 = y_1 - z_2 = \frac{n\gamma(n)}{n\gamma(n) + \beta + n\gamma(n)\beta + \beta^2} \left[ y_1 + \frac{y_2}{R} - \frac{\bar{z}_3}{R} + \frac{1}{n} \left[ \frac{y_3}{R} + \frac{\bar{z}_3 + y_4}{R^2} \right] \right],
\]

\[
c_2 = \beta R c_1,
\]

\[
c_3 = \frac{1}{\gamma(n)} c_2,
\]

29
\[ c_4 = \beta R c_3, \]
\[ b_2 = \frac{n \gamma(n)}{n \gamma(n) + \beta} \frac{1}{n} \left[ y_3 + R z_3 + \frac{y_1}{R} \right] - \frac{\beta}{n \gamma(n) + \beta} [R y_1 + y_2 - z_3], \]
\[ z_2 = \frac{\beta}{1 + \beta} y_1 - \frac{1}{1 + \beta} \left[ \frac{y_2}{R} - \frac{z_3}{R} + \frac{b_2}{R} \right], \]
\[ z_4 = \frac{\beta}{1 + \beta} (y_3 + R z_3 - n b_2) - \frac{1}{1 + \beta} \frac{y_4}{R}. \]

The comparative statics for income ratios in Proposition 3 are given by

\[ \frac{\partial b_2}{\partial y_1} = - \frac{\beta R}{n \gamma(n) + \beta} < 0, \]
\[ \frac{\partial b_2}{\partial y_2} = - \frac{\beta}{n \gamma(n) + \beta} < 0, \]
\[ \frac{\partial b_2}{\partial y_3} = \frac{\gamma(n)}{n \gamma(n) + \beta} > 0, \]

and

\[ \frac{\partial b_2}{\partial y_4} = \frac{\gamma(n)}{n \gamma(n) + \beta} \frac{1}{R} > 0. \]

For the case of borrowing limit \( z_3 \) we have

\[ \frac{\partial b_2}{\partial z_3} = \frac{\gamma(n) R + \beta}{n \gamma(n) + \beta} > 0. \]

Finally, for number of kids the comparative statics are given by

\[ \frac{\partial b_2}{\partial n} = \frac{\gamma'(n) \beta - \gamma(n)^2}{(n \gamma(n) + \beta)^2} \left[ y_3 + R z_3 + \frac{y_1}{R} \right] + \frac{\beta [\gamma(n) + n \gamma'(n)]}{(n \gamma(n) + \beta)^2} \left[ R y_1 + y_2 - z_3 \right] < 0, \]

where it can be shown that the expression above is negative because \( b_2 > 0 \) and \( \gamma'(n) < 0. \)

**TRANSFER TYPE 2 under condition (16)** - In this case the borrowing constraint binds in periods 1 and 2, but transfers to the child only occur in period 2, or

\[ b_2 > 0, b_1 = b_3 = 0, \]
\[ R_3 > R_2 > R_4 = R, \]
\[ z_3 = \bar{z}_3, \quad z_2 = \bar{z}_2, \quad \text{and} \quad z_4 \geq \bar{z}_4. \]
Equations (4) and (5) together with the budget constraints imply the following steady state solution,

\[ c_1 = y_1 - z_2, \]
\[ c_2 = y_2 + Rz_2 - z_3 + b_2 = \frac{n\gamma(n)}{1 + n\gamma(n) + \beta} \left[ y_2 + Rz_2 - z_3 + \frac{1}{n} \left( y_3 + Rz_3 + \frac{y_4}{R} \right) \right], \]
\[ c_3 = \frac{1}{\gamma(n)} c_2, \]
\[ c_4 = \beta Rc_3, \]
\[ b_2 = \frac{n\gamma(n)}{1 + n\gamma(n) + \beta} \left[ y_3 + Rz_3 + \frac{y_4}{R} \right] - \frac{1 + \beta}{1 + n\gamma(n) + \beta} \left[ y_2 + Rz_2 - z_3 \right], \]
\[ z_4 = \frac{\beta}{1 + \beta} \left[ y_3 + Rz_3 - nb_2 \right] - \frac{1}{1 + \beta} \frac{y_4}{R}. \]

The comparative statics for income ratios in Proposition 3 are given by

\[ \frac{\partial b_2}{\partial y_1} = 0 \]
\[ \frac{\partial b_2}{\partial y_2} = -\frac{1 + \beta}{1 + n\gamma(n) + \beta} < 0, \]
\[ \frac{\partial b_2}{\partial y_3} = \frac{\gamma(n)}{1 + n\gamma(n) + \beta} > 0, \]

and

\[ \frac{\partial b_2}{\partial y_4} = \frac{\gamma(n)}{1 + n\gamma(n) + \beta} \frac{1}{R} > 0. \]

For the case of borrowing limits \( z_2 \) and \( z_3 \) we have

\[ \frac{\partial b_2}{\partial z_2} = -\frac{(1 + \beta)R}{1 + n\gamma(n) + \beta} < 0, \]

and

\[ \frac{\partial b_2}{\partial z_3} = \frac{\gamma(n)R + 1 + \beta}{1 + n\gamma(n) + \beta} > 0. \]

Finally, for number of kids the comparative statics are given by

\[ \frac{\partial b_2}{\partial n} = \frac{\gamma'(n)(1 + \beta) - \gamma(n)^2}{(1 + n\gamma(n) + \beta)^2} \left[ y_3 + Rz_3 + \frac{y_4}{R} \right] + \frac{\gamma(n) + n\gamma'(n)}{(1 + n\gamma(n) + \beta)^2} \frac{1 + \beta}{1 + n\gamma(n) + \beta} \left[ y_2 + Rz_2 - z_3 \right] < 0, \]

where it can be shown that the expression above is negative because \( b_2 > 0 \) and \( \gamma'(n) < 0. \)

**TRANSFER TYPE 3** - In this case the borrowing constraint binds in periods 1 and 2, and
transfers to the child only in periods 1 and 2, or

\[ b_1, b_2 > 0, b_3 = 0, \]

\[ R_2 = R_3 > R_4 = R, \]

\[ z_2 = \bar{z}_2, \quad z_3 = \bar{z}_3, \quad \text{and} \quad z_4 > \bar{z}_4. \]

Equations (4) and (5) together with the budget constraints imply the following steady state solution,

\[
c_1 = \frac{\left( n\gamma(n) \right)^2}{1 + n\gamma(n) + (n\gamma(n))^2 + \beta} \left[ y_1 - \bar{z}_2 + \frac{1}{n} (y_2 + R\bar{z}_2 - \bar{z}_3) + \frac{1}{n^2} \left( y_3 + R\bar{z}_3 + \frac{y_4}{R} \right) \right],
\]

\[
c_2 = \frac{1}{\gamma(n)} c_1,
\]

\[
c_3 = \frac{1}{\gamma(n)} c_2,
\]

\[
c_4 = \beta R c_3,
\]

\[
b_1 = \frac{\left( n\gamma(n) \right)^2}{1 + n\gamma(n) + (n\gamma(n))^2 + \beta} \left[ \frac{1}{n} (y_2 + R\bar{z}_2 - \bar{z}_3) + \frac{1}{n^2} \left( y_3 + R\bar{z}_3 + \frac{y_4}{R} \right) \right] - \frac{1 + \beta}{1 + n\gamma(n) + (n\gamma(n))^2 + \beta} [y_1 - \bar{z}_2],
\]

\[
b_2 = \frac{n\gamma(n) + (n\gamma(n))^2}{1 + n\gamma(n) + (n\gamma(n))^2 + \beta} \frac{1}{n} \left[ y_3 + R\bar{z}_3 + \frac{y_4}{R} \right] - \frac{1 + \beta}{1 + n\gamma(n) + (n\gamma(n))^2 + \beta} \left[ n(y_1 - \bar{z}_2) + y_2 + R\bar{z}_2 - \bar{z}_3 \right],
\]

\[
z_4 = \frac{\beta}{1 + \beta} [y_3 + R\bar{z}_3 - nb_2] - \frac{1}{1 + \beta} \frac{y_4}{R}.
\]

The comparative statics for income ratios in Proposition 3 are given by

\[
\frac{\partial b_1}{\partial y_1} = -\frac{1 + n\gamma(n) + \beta}{1 + n\gamma(n) + (n\gamma(n))^2 + \beta} < 0,
\]

\[
\frac{\partial b_1}{\partial y_2} = \frac{n\gamma(n)^2}{1 + n\gamma(n) + (n\gamma(n))^2 + \beta} > 0,
\]

\[
\frac{\partial b_1}{\partial y_3} = \frac{(\gamma(n))^2}{1 + n\gamma(n) + (n\gamma(n))^2 + \beta} > 0,
\]

32
\[
\frac{\partial b_1}{\partial y_4} = \frac{(\gamma(n))^2}{1 + n\gamma(n) + (n\gamma(n))^2 + \beta R} > 0,
\]
\[
\frac{\partial b_2}{\partial y_1} = -\frac{1 + \beta}{1 + n\gamma(n) + (n\gamma(n))^2 + \beta n} < 0
\]
\[
\frac{\partial b_2}{\partial y_2} = -\frac{1 + \beta}{1 + n\gamma(n) + (n\gamma(n))^2 + \beta} < 0,
\]
\[
\frac{\partial b_2}{\partial y_3} = \frac{n\gamma(n) + (n\gamma(n))^2}{1 + n\gamma(n) + (n\gamma(n))^2 + \beta n} > 0,
\]
and
\[
\frac{\partial b_2}{\partial y_4} = \frac{n\gamma(n) + (n\gamma(n))^2}{1 + n\gamma(n) + (n\gamma(n))^2 + \beta nR} > 0.
\]

For the case of borrowing limits \( z_2 \) and \( z_3 \) we have
\[
\frac{\partial b_1}{\partial z_2} = \frac{n\gamma(n)^2 R + 1 + n\gamma(n) + \beta}{1 + n\gamma(n) + (n\gamma(n))^2 + \beta} > 0,
\]
\[
\frac{\partial b_1}{\partial z_3} = -\frac{(n - R)\gamma(n)^2}{1 + n\gamma(n) + (n\gamma(n))^2 + \beta} < 0, \text{ if } n > R,
\]
\[
\frac{\partial b_2}{\partial z_2} = \frac{(1 + \beta)(n - R)}{1 + n\gamma(n) + (n\gamma(n))^2 + \beta} > 0, \text{ if } n > R,
\]
and
\[
\frac{\partial b_2}{\partial z_3} = \frac{\gamma(n)R + n\gamma(n)^2 R + 1 + \beta}{1 + n\gamma(n) + (n\gamma(n))^2 + \beta} > 0.
\]

Finally, for number of kids the comparative statics are given by
\[
\frac{\partial b_1}{\partial n} = \frac{2n\gamma(n)(\gamma(n) + n\gamma'(n))(1 + n\gamma(n) + (n\gamma(n))^2 + \beta) - (n\gamma(n))^2(1 + 2n\gamma(n))(\gamma(n) + n\gamma'(n))}{(1 + n\gamma(n) + (n\gamma(n))^2 + \beta)^2}
\]
\[
\times \left[ \frac{1}{n} (y_2 + Rz_2 - z_3) + \frac{1}{n^2} \left( y_3 + Rz_3 + \frac{y_4}{R} \right) \right]
\]
\[
- \frac{(n\gamma(n))^2}{1 + n\gamma(n) + (n\gamma(n))^2 + \beta} \left[ \frac{1}{n^2} (y_2 + Rz_2 - z_3) + \frac{2}{n^3} \left( y_3 + Rz_3 + \frac{y_4}{R} \right) \right]
\]
\[
- \frac{(1 + n\gamma(n) + (n\gamma(n))^2 + \beta) - (1 + n\gamma(n) + \beta)(1 + 2n\gamma(n))}{[1 + n\gamma(n) + (n\gamma(n))^2 + \beta]^2} (\gamma(n) + n\gamma'(n)) [y_1 - z_2],
\]

where it can be shown that
\[
\frac{\partial b_1}{\partial n} < 0 \text{ if } 1 + \beta < \left[ \gamma n^{1-\varepsilon} + (1 + \beta)2 \right] \varepsilon n^{2\varepsilon}.
\]
In addition,

\[
\frac{\partial b_2}{\partial n} = \frac{(1 + \beta) (1 + 2n\gamma(n)) (\gamma(n) + n\gamma'(n))}{(1 + n\gamma(n) + (n\gamma(n))^2 + \beta^2)} \frac{1}{n} \left( y_3 + R \tilde{z}_3 + \frac{y_4}{R} \right) \\
- \frac{n\gamma(n) + (n\gamma(n))^2}{1 + n\gamma(n) + (n\gamma(n))^2 + \beta} \frac{1}{n^2} \left( y_3 + R \tilde{z}_3 + \frac{y_4}{R} \right) \\
+ \frac{(1 + \beta) (1 + 2n\gamma(n)) (\gamma(n) + n\gamma'(n))}{(1 + n\gamma(n) + (n\gamma(n))^2 + \beta^2)} [n (y_1 - \tilde{z}_2) + (y_2 + R \tilde{z}_2 - \tilde{z}_3)] \\
- \frac{1 + \beta}{1 + n\gamma(n) + (n\gamma(n))^2 + \beta} (y_1 - \tilde{z}_2),
\]

where it can be shown that \( \partial b_2 / \partial n < 0 \) if

\[
\frac{(1 + \beta) (1 + 2n\gamma(n)) (\gamma(n) + n\gamma'(n))}{1 + n\gamma(n) + (n\gamma(n))^2 + \beta} \left[ n (y_1 - \tilde{z}_2) + (y_2 + R \tilde{z}_2 - \tilde{z}_3) + \frac{1}{n} \left( y_3 + R \tilde{z}_3 + \frac{y_4}{R} \right) \right] \\
< \left[ n\gamma(n) + (n\gamma(n))^2 \right] \frac{1}{n^2} \left( y_3 + R \tilde{z}_3 + \frac{y_4}{R} \right) + (1 + \beta) (y_1 - \tilde{z}_2).
\]
| Linear estimation of the age profile of inter vivos transfers 1996-2014 |
|---|---|---|
| \(N=102,495\) | **OLS** | **Fixed effects** |
| | Probability | Transfer amount | Probability | Transfer amount |
| | Family fixed effects | Child fixed effects | Family fixed effects | Child fixed effects |
| **Linear age fit** | | | | |
| Age | -0.006*** | -39.0*** | -0.006*** | -0.005*** | -44.4*** | -30.4*** |
| Constant | 0.422*** | 2585.7*** | 0.404*** | 0.372*** | 2869.4*** | 2287.5*** |
| **Age brackets** | | | | |
| \(<30\) | 0.194*** | 1225.5*** | 0.106*** | 0.139*** | 609.5*** | 731.6*** |
| \(30-39\) | 0.073*** | 299.9*** | 0.020*** | 0.042*** | 89.7 | 166.4*** |
| \(40-49\) | 0.030*** | 198.2*** | 0.003 | 0.012*** | 34.9 | 60.3 |
| Constant | 0.096*** | 617.6*** | 0.118*** | 0.129*** | 747.7*** | 896.0*** |
| \(R^2\) | 0.026 | 0.007 | 0.330 | 0.422 | 0.284 | 0.352 |
| \(Adj. R^2\) | 0.293 | 0.336 | 0.244 | 0.255 |

Notes: Sample includes 102,664 observations of kid-parent pairs during 1996-2014. Omitted age bracket is 50+ years old. Transfer amount includes zero and positive amounts. Year dummies are included for OLS models and for family fixed effects. Standard errors are robust. Start superscripts: * \(p < 0.10\), ** \(p < .05\), *** \(p < 0.01\).
TABLE 2  
Two-part estimation of the age profile of intervivos transfers 1996-2014

<table>
<thead>
<tr>
<th>Linear fit</th>
<th>Two-part estimation</th>
<th>Fixed effects</th>
<th>Fixed effects</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Logit for probability (odds ratios)</td>
<td>OLS for positive amounts</td>
<td>Conditional logit for probability (odds ratios)</td>
</tr>
<tr>
<td></td>
<td>Family fixed effects</td>
<td>Child fixed effects</td>
<td>Family fixed effects</td>
</tr>
<tr>
<td>Age</td>
<td>0.953***</td>
<td>14.4</td>
<td>0.926***</td>
</tr>
<tr>
<td>Constant</td>
<td>5739.9***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age brackets</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;30</td>
<td>3.665***</td>
<td>-551.3</td>
<td>2.727***</td>
</tr>
<tr>
<td>30-39</td>
<td>1.854***</td>
<td>-1239.4***</td>
<td>1.371***</td>
</tr>
<tr>
<td>40-49</td>
<td>1.339***</td>
<td>-130.1</td>
<td>1.112***</td>
</tr>
<tr>
<td>Constant</td>
<td>6828.9***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adj $R^2$ / Pseudo $R^2$</td>
<td>0.027</td>
<td>0.003</td>
<td>0.023</td>
</tr>
<tr>
<td>N</td>
<td>102,495</td>
<td>14,956</td>
<td>69,315</td>
</tr>
</tbody>
</table>

Notes: Sample is same as in Table 1. Omitted age bracket is 50+ years old. The two-part estimation consists of a logit for the probability and OLS for the transfer amount conditional on receiving. Year dummies are included for the two part-estimation and the two-part family fixed effects. Standard errors are robust. Start superscripts: " p < 0.10, " p < 0.05, " p < 0.01.
### TABLE 3
Total transfers by period for 1967-71 cohort during 1996-2014

<table>
<thead>
<tr>
<th>Probability</th>
<th>Transfer amount</th>
<th>Conditional transfer amount</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Five periods – 2 waves per period</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Period 1</td>
<td>0.35</td>
<td>$3,238</td>
</tr>
<tr>
<td>Period 2</td>
<td>0.27</td>
<td>$2,496</td>
</tr>
<tr>
<td>Period 3</td>
<td>0.23</td>
<td>$2,271</td>
</tr>
<tr>
<td>Period 4</td>
<td>0.24</td>
<td>$2,521</td>
</tr>
<tr>
<td>Period 5</td>
<td>0.21</td>
<td>$1,666</td>
</tr>
<tr>
<td><strong>Two periods – 5 waves per period</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Period 1</td>
<td>0.46</td>
<td>$6,887</td>
</tr>
<tr>
<td>Period 2</td>
<td>0.36</td>
<td>$5,306</td>
</tr>
<tr>
<td><strong>Total transfers – 10 waves</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.56</td>
<td>$12,201</td>
</tr>
</tbody>
</table>

**Notes:** Sample includes adult children in the 1967-71 cohort who were born to parents in the Initial HRS cohort (1931-41). Sample size is 1,141 kid-parent pairs from 846 families observed for 10 waves during 1996-2014, when children receive transfers roughly at ages 25-45 years old. Dollar amounts are expressed in 2014 US$. The first set of statistics divides the sample in five periods (2 waves each period, or a 4-year window per period), while the second set reports the case of two periods (5 waves each period, or a 10-year window per period). Total transfers for all 10 waves (20-year period) are reported last.
### TABLE 4
Characterization of transfer types for 1967-71 cohort

<table>
<thead>
<tr>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Average conditional total transfer by period</strong></td>
</tr>
<tr>
<td>Period 1 – first five waves</td>
</tr>
<tr>
<td>Period 2 – second five waves</td>
</tr>
<tr>
<td><strong>Distribution by transfer types</strong></td>
</tr>
<tr>
<td>Type 0 – no transfers</td>
</tr>
<tr>
<td>Type 1 – positive transfer period 1</td>
</tr>
<tr>
<td>Type 2 – positive transfer period 2</td>
</tr>
<tr>
<td>Type 3 – positive transfer both periods</td>
</tr>
<tr>
<td><strong>Average conditional total transfer by transfer type</strong></td>
</tr>
<tr>
<td>Type 1 – positive transfer period 1</td>
</tr>
<tr>
<td>Type 2 – positive transfer period 2</td>
</tr>
<tr>
<td>Type 3 – positive transfer both periods</td>
</tr>
<tr>
<td>Transfer period 1</td>
</tr>
<tr>
<td>Transfer period 2</td>
</tr>
</tbody>
</table>

**Notes:** Sample includes 1,114 adult children in the 1967-71 cohort who were born to parents in the Initial HRS cohort (1931-41). Dollar amounts are expressed in 2014 US. Period 1 in the data corresponds to total transfers the first five waves (10 years), while period 2 are total transfers from the second five waves. For the 1967-71 cohort, period 1 encompasses child receiving transfers at ages 25 to 35, and period 2 at ages 35 to 45.
<table>
<thead>
<tr>
<th>Characteristics (% in sample)</th>
<th>Type 0</th>
<th>Type 1</th>
<th>Type 2</th>
<th>Type 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Average annual income of parents</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>First quartile ($40,098)</td>
<td>64.7%</td>
<td>17.2%</td>
<td>8.8%</td>
<td>9.3%</td>
</tr>
<tr>
<td>Second quartile ($68,902)</td>
<td>47.6%</td>
<td>20.7%</td>
<td>9.3%</td>
<td>22.4%</td>
</tr>
<tr>
<td>Third quartile ($104,972)</td>
<td>36.0%</td>
<td>25.0%</td>
<td>11.2%</td>
<td>27.7%</td>
</tr>
<tr>
<td>Fourth quartile ($465,084)</td>
<td>29.0%</td>
<td>18.3%</td>
<td>7.2%</td>
<td>45.6%</td>
</tr>
<tr>
<td><strong>Education level parent (head)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High school (41%)</td>
<td>41.3%</td>
<td>18.7%</td>
<td>11.1%</td>
<td>28.8%</td>
</tr>
<tr>
<td>Some college (24%)</td>
<td>44.0%</td>
<td>20.4%</td>
<td>9.1%</td>
<td>26.5%</td>
</tr>
<tr>
<td>College + (35%)</td>
<td>30.0%</td>
<td>25.9%</td>
<td>9.5%</td>
<td>34.5%</td>
</tr>
<tr>
<td><strong>Education level adult child</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High school (30%)</td>
<td>50.4%</td>
<td>16.0%</td>
<td>10.6%</td>
<td>23.1%</td>
</tr>
<tr>
<td>Some college (24%)</td>
<td>40.9%</td>
<td>21.3%</td>
<td>11.5%</td>
<td>26.3%</td>
</tr>
<tr>
<td>College + (46%)</td>
<td>37.4%</td>
<td>24.1%</td>
<td>8.5%</td>
<td>30.0%</td>
</tr>
<tr>
<td><strong>Number of siblings</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Zero (7%)</td>
<td>27.9%</td>
<td>29.0%</td>
<td>16.4%</td>
<td>26.7%</td>
</tr>
<tr>
<td>One (26%)</td>
<td>32.0%</td>
<td>21.9%</td>
<td>8.8%</td>
<td>37.3%</td>
</tr>
<tr>
<td>Two (24%)</td>
<td>42.6%</td>
<td>18.8%</td>
<td>9.0%</td>
<td>29.6%</td>
</tr>
<tr>
<td>Three or more (43%)</td>
<td>56.0%</td>
<td>18.8%</td>
<td>8.2%</td>
<td>17.0%</td>
</tr>
</tbody>
</table>

Notes: Sample includes 1.1.41 adult children in the 1967-71 cohort who were born to parents in the Initial HRS cohort (1931-41). Transfer types correspond to those described in Table 4.
### TABLE 6

*Multinomial logit for transfer types for the 1967-71 cohort*

*Base outcome – transfer type 0*

<table>
<thead>
<tr>
<th>Transfer type</th>
<th>Relative risk ratio</th>
<th>Robust standard error</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Transfer type 1</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Parental average income</td>
<td>0.992</td>
<td>0.021</td>
<td>0.712</td>
</tr>
<tr>
<td>Parental years of schooling</td>
<td>1.110</td>
<td>0.045</td>
<td>0.011</td>
</tr>
<tr>
<td>Child years of schooling</td>
<td>1.110</td>
<td>0.055</td>
<td>0.039</td>
</tr>
<tr>
<td>Number of siblings</td>
<td>0.850</td>
<td>0.045</td>
<td>0.002</td>
</tr>
<tr>
<td><strong>Transfer type 2</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Parental average income</td>
<td>1.046</td>
<td>0.016</td>
<td>0.003</td>
</tr>
<tr>
<td>Parental years of schooling</td>
<td>1.063</td>
<td>0.041</td>
<td>0.115</td>
</tr>
<tr>
<td>Child years of schooling</td>
<td>0.967</td>
<td>0.058</td>
<td>0.575</td>
</tr>
<tr>
<td>Number of siblings</td>
<td>0.815</td>
<td>0.063</td>
<td>0.009</td>
</tr>
<tr>
<td><strong>Transfer type 3</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Parental average income</td>
<td>1.048</td>
<td>0.026</td>
<td>0.061</td>
</tr>
<tr>
<td>Parental years of schooling</td>
<td>1.114</td>
<td>0.041</td>
<td>0.003</td>
</tr>
<tr>
<td>Child years of schooling</td>
<td>1.030</td>
<td>0.047</td>
<td>0.523</td>
</tr>
<tr>
<td>Number of siblings</td>
<td>0.739</td>
<td>0.041</td>
<td>0.000</td>
</tr>
</tbody>
</table>

*Likelihood ratio chi-square = 106.97*

*Prob > chi-square = 0.000*

**Notes:** Sample includes 1,141 adult children in the 1967-71 cohort. Transfer types correspond to those described in Table 4.
<table>
<thead>
<tr>
<th></th>
<th>Linear estimation</th>
<th>Two-part estimation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Probability</td>
<td>Transfer amount</td>
</tr>
<tr>
<td>Parental average income</td>
<td>0.006**</td>
<td>746.6***</td>
</tr>
<tr>
<td>($10,000s)</td>
<td>(0.003)</td>
<td>(263.0)</td>
</tr>
<tr>
<td>Parental years of schooling</td>
<td>0.022**</td>
<td>514.8</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(356.2)</td>
</tr>
<tr>
<td>Child years of schooling</td>
<td>0.011</td>
<td>446.1</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(411.6)</td>
</tr>
<tr>
<td>Number of siblings</td>
<td>-0.049***</td>
<td>-1562.1***</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(330.6)</td>
</tr>
<tr>
<td>N</td>
<td>1,090</td>
<td>1,090</td>
</tr>
<tr>
<td>$R^2$ / Pseudo $R^2$</td>
<td>0.11</td>
<td>0.10</td>
</tr>
</tbody>
</table>

Notes: Sample includes 1,141 adult children in the 1967-71 cohort who were born to parents in the Initial HRS cohort (1931-41). Sample size is 1,141 kid-parent pairs from 846 families. Standard errors in parenthesis (* p < 0.10, ** p < 0.05, *** p < 0.01). Additional control variables include child’s gender and parent’s race.
Notes: Sample includes 1,141 kid-parent pairs from the 1967-71 cohort observed during 1996-2014. Transfers are observed for a total of 10 waves (each other year). The left panel portrays the frequency by which 0, 1, 2, etc. transfers are received during the observed period. The right panel portrays the frequencies by which 1, 2, 3, etc. transfers are received.
Notes: Sample includes 1,141 kid-parent pairs from the 1967-71 cohort observed during 1996-2014. Transfers are observed for a total of 10 waves (each other year). Each panel corresponds to a total number of times transfers are received by the adult child during those 10 waves. Each panel portrays the distribution of years in which the first transfer was received during the observed period.
Notes: Sample includes 1,141 kid-parent pairs from the 1967-71 cohort observed during 1996-2014. Transfers are observed for a total of 10 waves (each other year). Each panel corresponds to a total number of times transfers are received by the adult child during those 10 waves. Each panel portrays the distribution of years between the received transfers.
Notes: The top panel illustrates examples of income profiles that generate the transfer types in the bottom panel. Amounts are normalized to period-1 income.
Figure 5. Examples of transfer patterns for various scenarios

Notes: The figure assumes the income profile generating transfer type 1 in Figure 4. Each panel illustrates the transfer patterns that would emerge under different scenarios, one at a time. Amounts are normalized to period-1 income.