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Dynamic aspects of family transfers ☆

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ABSTRACT

Parents transfer a great deal to their adult children, and we have rich theoretical models providing a framework for these transfers. However, both the models and existing empirical work typically examine behavior in the cross section. To date, we know little about the dynamic aspects of family transfers. Here I examine transfers over a span of 17 years and find substantial changes in recipiency over time and a strong negative correlation between transfers and transitory income. I also find that events such as job loss and divorce are strong predictors of parental transfers and, although rare, are typically associated with larger transfers than income alone might predict. Finally, transfers are distributed unequally across siblings, and perhaps surprisingly, the distribution of transfers becomes even more unequal when examined over an extended period of time than in any single year. The evidence presented here thus suggests that dynamic analyses can provide insights into behavior that are impossible to obtain in a static context.

1. Introduction

Intergenerational transfers between family members are an important economic phenomenon, particularly those transfers from parents to children. Gale and Scholz (1994) estimate yearly flows between parents and their non-coresident children of $65 billion in 2010 dollars. Such transfers are likely to have a substantial impact on the well-being of both donors and recipients and will have consequences for the distribution of wealth. Similarly, familial transfers may interact with public transfers, and in doing so could alter the effectiveness and eventual beneficiaries of government transfer programs.

While economists have developed important theoretical models of transfer behavior, as an empirical matter, we actually know very little. Recent work has begun to document some of the patterns but much remains to be learned. Most importantly, nearly all studies to date have been limited to cross sectional patterns of giving. While this static framework mimics the style of models underlying the analyses, it misses important features of the data. Capturing transfers at a single point in time makes it difficult to understand how parents respond to various events in a child's life or to understand the cumulative importance of transfers when aggregated over an extended period of time. Even simple questions such as the year-to-year variation in receipt of transfers have remained unanswered, so it is unclear whether the same children benefit year-in and year-out or whether transfers benefit a large number of children on a less regular basis. Similarly, an assessment of how transfers are allocated among siblings done at a single point in time is unlikely to convey conclusive information about the lifetime distribution of transfers.[1]

Looking beyond simple descriptive statistics to assess what factors are associated with transfers can be problematic in that there are many characteristics of a child that are well-known to parents but not observable to analysts. Attributes such as a child's industriousness or ability may affect transfers as might financial measures such as permanent income. Unfortunately, these variables are not typically observed in data.[2]

In this paper I address these issues by providing some of the first empirical evidence of transfers over a prolonged period of time. I draw on data from the Health and Retirement Study (HRS) covering the time period 1992–2008 to assess the time varying nature of

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[1] Indeed, it is often speculated that the degree of inequality in the distribution of transfers among siblings shown in earlier work would be mitigated greatly with a longer period of observation.

[2] Altonji et al. (1997) do an excellent job in constructing a measure of permanent income based on reported income in the PSID.

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0047-2727/

transfers and to compare aggregate patterns of giving with cross-sectional results. Furthermore, by examining multiple observations within families and over time, I am able to control for unobserved family and child effects, such as parental generosity or a child's ability or industriousness, to obtain unbiased measures of the relationships between observable characteristics such as income and transfers.

Looking over a 17 year period, I find considerable variation in transfers over time. In each year approximately 14% of children receive a transfer from their parents, yet only 6% of the sample receives a transfer in any two consecutive survey periods. Furthermore, while 46% of children in my sample receive a transfer in at least one period, less than 1% receive a transfer in each of the nine waves of the survey. This result contrasts sharply with perceived wisdom that some children receive transfers year-in and year-out. These dynamic aspects of behavior are missed in cross sectional studies, yet from the analyses presented here they appear to be an important part of the story.[3] Transfers made in conjunction with specific events in the child's life appear to be common and suggest that parents frequently respond to negative shocks. Of particular importance is the loss of a job or a spouse. Perhaps most surprisingly, differences in the amounts received by siblings in any one year do not appear to "average out" over time. Rather, the amount given to siblings becomes less equal when examining a larger window of time than in a simple cross section.

Finally, in examining transfer behavior net of unobserved differences across children, I find that the effect of a child's current income on transfers is large and significantly different from zero, but is approximately one-third smaller than its effect in specifications that do not control for unobservable differences. These results indicate a strong negative correlation between transfers and the transitory income of the potential recipient as well as a negative relationship between transfers and unobserved characteristics of the child such as ability or permanent income. This latter insight demonstrates the necessity of adequate controls for permanent income and other fixed attributes in our models.

The remainder of the paper is organized as follows: In Section 2, I briefly outline the standard theoretical model and discuss the existing literature. Section 3 describes the data I use in the empirical work and provides interesting descriptive patterns. Section 4 discusses the estimated effects of current income and other observable characteristics on transfers in the context of regression models. A final section concludes and summarizes the results.

2. Background and theory

2.1. Standard altruism model

The primary theoretical framework for understanding parental transfers has been an altruism model. In the standard altruism model parents care about the well-being of their children; parents receive utility from their own consumption and from the utility of their children. Following the specification used in Cox (1987), the utility function of a parent is written as $U_p = U_p(c_p, V(c_k))$ where c_p and c_k are the consumption of the parent and child, respectively. The consumption of the child is determined by his own income y_k and transfers from the parent T. Thus, $c_k = y_k + T$.

The central prediction of this model is that the change in transfers for a change in a child's income is negative ($\frac{\partial T}{\partial y_k} < 0$); as the child's income increases, the marginal utility of an additional dollar of consumption decreases, and the parent transfers less. This result implies that in families with more than one child, parents will make greater transfers to lower income children, in effect compensating the lower income children for their lack of resources and endeavoring to equalize the marginal utility of consumption across children.[4]

In this strict interpretation of altruism, the comparative statics also predict that if transfers are positive, an increase of one dollar in the child's income along with a decrease of one dollar in the parent's income, will result in a decrease of one dollar in transfers to the child.[5] That is, $\frac{\partial T}{\partial y_k} - \frac{\partial T}{\partial w_p} = -1$ where w_p is the income of the parent.

Given the predictions, empirical tests of the model have centered on the estimates of $\frac{\partial T}{\partial y_k}$ and $\frac{\partial T}{\partial w_p}$. While early work found a *positive* relationship between a child's income and the amount of a transfer (Cox, 1987, Cox and Rank, 1992), a contradiction of the negative relationship predicted by the altruism model, more recent efforts with higher quality data have found a strong negative relationship (e.g. Cox and Jappelli, 1990, McGarry and Schoeni, 1995, 1997), a result consistent with the altruism model, but with alternative models as well.[6] Although the sign of $\frac{\partial T}{\partial y_k}$ found by these studies is consistent with the altruism model, the magnitudes of $\frac{\partial T}{\partial y_k}$ and $\frac{\partial T}{\partial w_p}$ (where estimated) fail to satisfy the derivative restriction, with estimates of $\frac{\partial T}{\partial y_k} - \frac{\partial T}{\partial w_p}$ that are closer to 0 than to −1.

2.2. Static versus dynamic outcomes

The model outlined above is presented in a static framework. In the context of a single period, parents know the lifetime earnings of their children and as noted, the consumption of a child is the sum of earnings and transfers. Parents make greater transfers to children with lower lifetime incomes and the timing of earnings and transfers is not an issue. However, in a multi-period framework, the timing of transfers becomes an important matter.

As highlighted by Altonji et al. (1997), absent additional constraints, if the child's permanent income is uncertain a parent will delay transfers in order to obtain additional information and more efficiently allocate resources. Similarly, a parent who is uncertain of her own date of death or future needs will be reluctant to part with resources she herself might need some day and will prefer to postpone transfers (Davies, 1981). Acting against the desire to postpone transfers is the possibility that children are liquidity constrained and unable to smooth consumption optimally across time. Even children with high *lifetime* incomes may be the recipients of inter vivos transfers if they are temporarily liquidity constrained and unable to attain the level of consumption predicted by their permanent incomes (Cox, 1990). Thus one would expect a negative relationship between transfers and current income and a positive relationship between

[3] Dunn (1997), and Rosenzweig and Wolpin (1994) are exceptions, both using multiple waves of the NLS surveys. However, information is not available on all siblings of the (potential) recipients, so a complete understanding of the allocation within families is not possible. More recently, Hochguertel and Ohlsson (2009) use multiple waves of the HRS to examine family transfers in regressions with a rich error structure and find that gifts are strongly compensatory.

[4] This simple model treats income as exogenous, but expanded models allow that individuals behave strategically, for instance reducing income in order to receive larger transfers (e.g. Bergstrom, 1989, Bruce and Waldman, 1990). In the context of the family, such shirking may well be observed by parents. In the empirical work that follows, I do not model a behavioral response from the child but control for child fixed effects which could include factors such as industriousness.

[5] See Cox (1987) for a derivation. Numerous variants of the altruism model have been developed which do not share this prediction. (See for example, Alger and Weibull, 2010;Karlan et al., 2009.) I note the prediction here as it has been the focus of several classic papers on this topic.

[6] The most frequently cited alternative to the altruism model is an exchange model wherein observed transfers represent payment for services provided by the child. In the exchange model parents care about their own utility and the services (s) provided by the child. Formally, $U_p = U(c_p, s)$. In an exchange regime the sign of the relationship between income and the magnitude of a transfer is indeterminate. As a child's income increases, the price of his time increases and the quantity of time purchased therefore declines. However, the net amount spent by the parent to purchase services (price × quantity) can either increase or decrease depending on the elasticities of supply and demand for services.

transfers and indicators of liquidity constraints. The extension to multiple periods makes testing of the model based on the simple derivative restriction problematic. While the model speaks to the relationship between transfers and changes in *permanent* income, the same relationship need not exist with respect to *current* income in a dynamic context.[7] Much insight into the dynamic aspects of giving thus depends on an empirical analysis.

In what follows, I focus on the responsiveness of transfers to changes in a child's income as well as to other dynamic elements in the child's life, such as changes in their family situation and employment—events which may lead the parent to update her expectations regarding the needs of the child and which may also signal the existence of liquidity constraints. Although the altruism model centers on income as the determinant of transfers, casual empiricism (or introspection) suggests that parents also make financial transfers for special events in a child's life, some of which might have *positive* implications for income (e.g. graduation from college). These gifts are consistent with a broader interpretation of altruism wherein the parent is incentivizing a child to behave in a desired manner, but are also consistent with other motivations (c.f. Mauss, 1925 on the importance of gifts in strengthening social ties).

3. Data

The data used in this paper come from the Health and Retirement Study (HRS). The HRS is a panel survey of the older U.S. population that began in 1992 with a sample of individuals born between the years 1931 and 1941 and their partners or spouses. When appropriately weighted the sample is representative of the U.S. population of the target cohort. The initial wave of questioning included 12,652 respondents in 7703 families. The second wave followed in 1994 with biennial interviews conducted ever since.

The original HRS sample has been augmented over time with additional cohorts including both older and younger age groups, making it approximately representative of the population ages 50 and over. For the analysis in this paper, however, I limit my attention to the initial respondents (and their children) in order to have as long a panel as possible. For a similar reason I also require that the household remain in the sample for the entire nine waves. While this requirement induces some selection bias, I control for a large set of observable characteristics of the parents in the regression analyses including income, wealth, and health, and use family fixed effects analysis to study changes net of fixed differences across families. Selection is also less problematic than might first appear in that the family remains in the sample as long as at least one spouse survives.[8] Finally, I also delete a small number of families in which the parents divorce and there is more than one parent providing information on the child.[9] This final exclusion allows me to avoid confounding the effects of interest with changes in behavior resulting from unanticipated changes in the motivation of parents due to the split.

The HRS is uniquely suited to a study of transfer behavior for several reasons. First, individuals in this age group are particularly likely to be making inter vivos transfers (Schoeni, 1993). Second, the HRS has specific questions about transfers to *each* child which likely result in more complete reporting than the more general questions about financial assistance to individuals outside the household that are used in many surveys (McGarry and Schoeni, 1995). Finally, there is relatively detailed information on *each* child in the family allowing for a complete within-family analysis.

There are a total of 3776 families in my sample with 12,835 children. I further restrict this sample to children ages 18 or older in the first wave in order to avoid counting legally required support payments to minor children as transfers, and to children who were not coresiding with the parent at the first interview, primarily to ensure that the children had in some sense transitioned to adulthood by living on their own for at least some period of time. With these selection criteria I have a sample of 3383 families with 10,064 children and 90,576 person years of observations.

4. Descriptive results

4.1. Cross sectional patterns

The means and standard errors for several of the variables used in the subsequent analyses are presented in Table 1. The first pair of columns reports the values for 1992, the first year of data; the second column gives the values for the same children in 2008, the last year; and the final column corresponds to the stacked data for all 90,576 person years of observations.

As one can see from the list of variables included in the table, there is a good deal of information available for the children of the HRS respondents. Respondents are asked to report the family incomes for each of their children, as well as each child's age, sex, whether they own a home, where they live with respect to the parent, their marital status, number of own children, the highest grade completed and whether they are currently enrolled in school, among others. The majority of these variables are measured in every wave of the survey although there are some differences in the set of questions across the years.

Most pertinent to the analysis in this paper is the measurement of income. The family income of children is measured categorically in the HRS.[10] The categories have evolved somewhat over time, changing slightly to capture better the range in the underlying distribution. However, the brackets have been constant since 1998 at incomes of less than $10,000, $10,000–$35,000, $35,000–$70,000 and greater than $70,000. I use these income categories to form two measures of income each of which allows for comparisons across waves. First, for each child in each wave, I use a single imputed value calculated as the median income within the given range for individuals in the CPS data.[11] This procedure provides me with a single number that makes examining changes over time and interpreting regression coefficients more straightforward. As a second measure, I take the various income categories and form four relatively consistent categories across waves. For example, I treat $10,000–$35,000 (used in most waves) and $10,000–$25,000 (used in the first wave only) as being the same category. While I rely primarily on the first method for ease of presentation, all analyses were done using both methods and with the sample limited to observations from the 1998 to 2008 surveys wherein the categories are identical across waves. The conclusions are unchanged. Finally, although this is a crude measure of income, there is a surprising amount of movement across categories

[7] See McGarry (2012) for a simple extension along these lines.

[8] As a check of the robustness of the results, the analyses in this paper have been repeated with observations from all cohorts and for all children for whom there were at least two waves of data, as well as for several alternative selection mechanisms including: limiting the sample to only those children who were never observed to coreside with a parent, and using observations for just the period from 1998 to 2008. I also experimented with expanding the sample to add children as they turn age 18 as well as including those who initially live at home. The conclusions are not sensitive to the sample selection criteria.

[9] In the case of divorce or separation, the HRS follows both respondents and asks the same questions about their children.

[10] An exception was made in the 1994 and 1996 waves which first asked for a continuous value and then provided the respondent with categorical responses if the respondent could not give an exact value. Income for the children in this original cohort was not obtained in 1998 or 2006.

[11] These data and the imputations were developed in concert with Steven Haider (see Haider and McGarry, 2012).

Table 1
Means of selected variables for sample of children.

	1992		2008		All	
	(n = 10,064)[a]		(n = 10,064)[a]		(90,576)[a]	
	Mean	Std err	Mean	Std err	Mean	Std err
Total family income of child:						
Less than $10,000	0.17	0.004	0.04	0.002	0.07	0.001
$10–$25/35,000	0.36	0.005	0.12	0.003	0.22	0.002
$25,000 or more	0.47	0.005	–	–		
$35,000–$70,000	–	–	0.23	0.004	0.25	0.002
$70,000	–	–	0.24	0.004	0.21	0.002
Parent reported don't know			0.37	0.005	0.25	0.002
Continuous measure	43,320	268.4	68,228	462	57,665	152
Demographic variables for child:						
Age	30.9	0.054	46.9	0.054	38.9	0.025
Male	0.503	0.005	0.50	0.005	0.50	0.002
Own home	0.47	0.005	0.67	0.005	0.59	0.002
Lives w/in 10 miles	0.40	0.005	0.29	0.005	0.33	0.002
Married	0.64	0.005	0.72	0.004	0.69	0.002
Number children	1.36	0.013	2.13	0.015	1.79	0.005
Schooling level	13.08	0.022	13.37	0.023	13.29	0.007
In school	0.08	0.003	0.03	0.002	0.04	0.001
Transfers:						
Received a transfer	0.15	0.004	0.12	0.003	0.14	0.001
Amount	1173	55.3	878	115.1	928.1	19.9
Amount >0	7977	324	7507	677	4524	92.3
Family variables:						
Income	63,020	659	49,293	704	58,766	261
Assets	275,976	5621	425,145	9655	381,169	3727
Nonwhite	0.20	0.004	0.20	0.004	0.20	0.001
Education	11.9	0.031	11.9	0.031	11.9	0.001
Number children	4.69	0.024	4.68	0.025	4.73	0.001
Poor health	0.11	0.003	0.15	0.004	0.08	0.001
Married	0.79	0.004	0.58	0.005	0.71	0.002
Unmarried female	0.18	0.004	0.35	0.005	0.25	0.001

Sample is of children ages 18years old or older in 1992, who do not live with their parents in that year and who are observed in all waves of the survey. Financial variables are reported in 2008 dollars.

[a] Number of observations differs for some variables due to missing values.

from one wave to the next, consistent with the age of the children in the sample.[12]

As is apparent in Table 1, when comparing the distribution of observations across income categories in 1992 and 2008, there is a significant increase in the incomes of adult children over time. In 1992, 17% of children had incomes below $10,000 while just 4% had incomes in this range in 2008. The second two categories differ somewhat between waves but the trend of rising incomes is clear: 36% had income between $10,000 and $25,000 in 1992 and a substantially smaller number, just 12%, had income in the $10,000–$35,000 range in 2008 despite it being much wider. Age obviously increased over time, but there were also large increases in home ownership, from 47% to 67%, and a decline in the fraction of children living within 10 miles of the parent, all consistent with the aging of the sample.

The HRS was particularly innovative in asking about familial transfers. It asked respondents to report financial assistance of $500 or more made to any child since the last survey, a time span of approximately two years.[13] Despite the maturing of the children, including rising incomes and increasing home ownership, a substantial fraction continues to receive transfers from their parents: 15% of children in 1992 and 12% in 2008 received a transfer from their parents—a surprisingly large fraction given that these children are nearly 50 years old on average in this final year. The mean amount (after adjusting for inflation) is much larger in 2008 consistent with increases in the resources of parents as well as with a worsening of parental health that provides opportunities for exchange-based transfers or estate planning.[14] Although there is somewhat of a decline in transfer receipt between the first and last waves of data, it is not indicative of a trend in the data; at any given interview,

[12] A child's income is reported by his parent. Because I am examining the relationship between a child's income and parental transfers, it is the parent's perception of that income that is relevant, even if it differs from actual income. Despite the possibility of measurement error, the income reported in the HRS appears to be a valid measure. It varies with schooling, gender, marital status, and race as one would expect. The distribution of reported income also compares well with the distribution for a similarly aged sample in the CPS. Conditional on a non-missing report of income in the HRS, 6% of children have incomes below $10,000 in 2008. In the CPS, the fraction is 5.4%. For the $10,000 to $35,000 categories the fractions are 19% and 18.3% for the HRS and CPS, respectively. The two distributions differ slightly in the two highest categories: 36.5% of HRS children have income between $35,000 and $70,000 compared to just 28% of those in the CPS (and thus 38% versus 48% at the top).

[13] In the first interview, transfers pertain to the previous year. I adjusted these amounts to control for the difference in the relevant time spans. In 1994 the lower bound was $100; I exclude transfers between $100 and $500 to mimic the cut-off point in other waves. If the respondent asked for clarification about what was to be included, they were told to include support, gifts and loans. Work elsewhere (MacDonald 1990) suggests that loans are rarely repaid. Hochguertel and Ohlsson (2009) similarly conclude that these inter vivos transfers are not loans.

[14] Gifts and bequests over a fixed amount may be subject to estate taxes. In 2008 this limit was $2 million. Individuals can spend down to reduce the amount subject to tax by making inter vivos transfers in amounts of less than an annual exclusion ($12,000 in 2008). One might thus expect wealthy parents to behave strategically and give gifts of this amount annually (Joulfaian, 2005, Kopczuk, 2013). In practice few families in the data are likely to be subject to the estate tax (just 2% in 2008) and previous work suggests that even those whose estates are likely to be taxed, fail to take advantage of the opportunity for tax-free giving (Poterba, 2001, and McGarry, 2001a,b.)

Table 2
Number[a] (and percent) receiving transfers in each year child level.

	Year 2 status		
Year 1 status	Received transfer	No transfer	Total
Transfer	4950 (6.2)	5968 (7.5)	10,918 (13.7)
No transfer	5667 (7.1)	62,950 (79.2)	68,617 (86.3)
Total	10,617 (13.4)	68,918 (86.7)	69,952 (100.0)

[a] The sample size differs from Table 1 due to missing observations on transfer receipt in one of the two comparison waves and the lack of Year 2 measures for data from 2008.

approximately 12–15% of children are reported to be receiving a transfer.[15]

While I examine only transfers flowing from a parent to a child, the survey also collects information on transfers received from children. These upstream transfers are far less common. Furthermore, it is exceedingly rare for transfers to flow in both directions, even when examining an extended period of time, and they are not explored here.[16]

4.2. Changes over time

Cross-sectional results reported above provide important information on the ties between families: Transfers are common and fairly large, and they appear to be relatively stable across time despite the aging of the sample. In work presented elsewhere (McGarry and Schoeni, 1995, 1997) we have also seen a strong negative relationship between transfers and the child's income, and a strong positive relationship between transfers and parental resources. Missing from these descriptions, and from nearly all of the evidence on this type of behavior, is an understanding of how transfers evolve over time: how they change in response to changes in the situation of the parent or child, whether the same children benefit year in and year out or whether the 12-15% recipiency rates seen above include a much larger fraction of children receiving a transfer in at least some years. In the remainder of the paper I explore these issues paying particular attention to the importance of the child's income and shocks to that income from life course events, as income figures prominently in our behavioral models and anecdotal evidence from the recent recession suggests that families may act to mitigate the effects of such shocks.

Table 2 begins this analysis by showing that there exists considerable variation in the receipt of transfers from wave to wave. As shown in the table, 55% of children who received a transfer in one two-year period did not receive anything in the following survey wave (7.5/13.7), and 53% of those who received a transfer in the second wave had not received one in the previous two-year period (7.1/13.4). Just six percent of the children in the sample received a transfer in two consecutive waves. For those children who received a transfer in both waves, the correlation between the two amounts is 0.14 (not shown), significantly different from zero but perhaps lower than might be expected.

In examining the frequency of transfers across waves, 46% of children received a transfer in at least one wave, 18% received a transfer in exactly one wave and only a tiny fraction, less than one percent, received transfers in all waves. Fig. 1 reports the conditional distribution of the number of survey years in which a child reportedly received a transfer. The most common outcome among recipients is

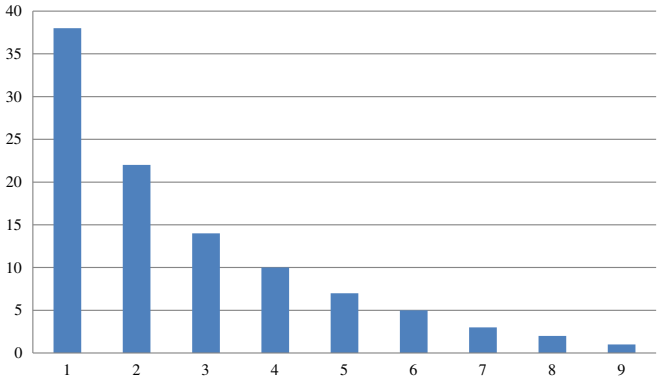

Fig. 1. Percentage of children receiving a transfer for a given number of survey waves.

for a transfer to occur just once over the entire time period (38%) and the receipt of transfers in every year is a vanishingly rare event (one percent). This irregularity of transfer receipt comes as a bit of a surprise give anecdotal stories of children who repeatedly receive financial gifts from their parents.[17]

The apparent idiosyncratic nature of transfers suggests that many transfers may be made in response to specific shocks to income or specific events rather than simply low income. Table 3 shows the relationship between changes in the child's income (measured categorically) and changes in the receipt of transfers across any two consecutive surveys. Those who did not receive a transfer in either wave are excluded from the table. For children whose income decreased between waves (and who had a non-zero transfer in at least one wave), the majority, 52%, had an increase in transfers (not adjusted for the CPI in this case) while 45% had a decline in transfer amounts. The relationship is similar for those children with an increase in income; 52% had a decrease in transfer amounts and 44% had an increase. Among those children whose income remains in the same bracket, the percentages experiencing an increase and a decrease in the transfer amount are nearly identical.

Obviously characteristics of the child other than income also change across waves. As these children age from an average age of 31 in 1992 to 49 in 2008 they experience various milestones in their lives—graduation from college (which I defined here as attaining 16 years of schooling), marriage, the purchase of a home, the birth of a child, and less happy outcomes: the end of a marriage, loss of a job, or loss of a home. Table 4a examines the relationship between transfers and these various events. The first column shows the average change in income for those children who experience the event measured relative to those who do not experience it. The next two pairs of columns show the probability and amount of a transfer for those making the transition in that wave and, secondly, for the portion of the sample that did not.

For those experiencing any of these life course events, both the probability and amount of the transfer are greater than for those not. Taking the events in turn, college graduation appears to be associated with the one of the highest probabilities of a transfer; 20% of children who completed 16 years of schooling between waves of the survey received a transfer at that time, a probability that is 50% greater than the probability for those who did not attain 16 years of schooling. Note that the transfer questions in the HRS ask about financial help or gifts and could therefore potentially include money given to finance an education as well as a graduation gift, or alternatively, assistance with starting out on their own upon completion

[15] Transfers to grandchildren are included in the measure of transfers to the child, and could thus account, in part, for the continued prevalence of transfers as children age. I control for the number of grandchildren in the regression analyses.

[16] In only three percent of the families are transfers observed to flow both from parents to children and from children to parents at least once during the entire 17 year period.

[17] Note that while the annual exclusion would provide a tax incentive for regular giving, few in this sample are likely to be faced with the prospect of estate taxes (Footnote 14).

Table 3
Relationship between change in income and change in transfers.

	Change in transfer amount				
Change in income	Decreased	No change	Increase	Total	Receiving transfer
Decreased:					
Number	1657	110	2901	3668	2522
Percent	45.2	3.0	51.8	100	68.6
Same:					
Number	2375	164	2373	4912	3156
Percent	48.4	3.3	48.3	100	64.0
Increased:					
Number	1892	118	1598	3608	2200
Percent	52.4	3.2	44.3	100	60.8

Rows may not sum to 100 due to rounding. The sample consists of children receiving a transfer in at least one of the two waves. Income changes are changes in reported income category (see text) and dollar value of transfers for this table only are in nominal terms—if real dollars are used there are only a couple of observations in the middle column with exactly equal transfers in both periods.

of schooling. However, the average amount of the gift is only $400 greater than for the non-graduating children ($7104 versus $6707)—consistent with a relatively small but meaningful gift as one might expect at graduation time.

The marriage of a child is associated with a large increase in the probability of a transfer at that time, approximately 30% greater than that for children who did not marry between waves, but perhaps surprisingly, only a small difference in the conditional amount transferred. In contrast, the purchase of a home is associated with a modest increase in the probability of a transfer but when gifts are made, the average is $800 greater.

The birth of a child is associated with a large difference in conditional amounts, $7275 for those children who had a child, versus $6745 for those who did not, although there is only a slight difference in the likelihood of a transfer being made at this time, 14.5% versus 13.4. One might suspect that in addition to financial transfers, transfers benefiting a grandchild may also be made in-kind, and gifts of clothes, toys, or furniture may not be included in this total. This possibility could help explain why the increase in the probability of giving is small.

While the birth of a grandchild, the purchase of a home, and marriage do not appear to be associated with a decline in average income, they may result in significant expenses incurred by the child, and an increase in the marginal utility of income. However, rather than making transfers for financial reasons, many of these transfers may well be made simply to mark a happy event. In contrast, other events—the loss of a job, a divorce, or the loss of a home—speak to an associated decline in income, and transfers here might respond to that shock.

In this sample the average change in family income across the waves for those children who experienced a job loss relative to those who did not, is approximately −$6800, approximately 10% of average income in 2008 and a greater percentage in earlier periods.[18] Job loss is also associated with a greater probability of a transfer than are any of the previously listed events except for schooling, and the amount is larger than all events other than the birth of a child. Among those working in one wave and not in the next, the probability of transfer receipt is 17.5% and the conditional amount averages $7454, again larger than any of the happier events.

However, the greatest probability of a transfer by far is associated with the end of a marriage. Among those children who were reportedly married in one wave and not in the next, the probability of receiving a cash transfer from a parent was 21%, 61% higher than for those who did not leave a marriage.[19] The income change experienced by these children, relative to those whose marriage does not end is also large, the largest among all events, equal to a decline of just over $17,000, but there is no difference in the conditional amount of transfers received. Although less obviously a negative shock, children who transition from owning a home to not owning one also experience a decline in income ($8700), are more likely than average to receive a transfer and receive somewhat larger amounts.

Because transfers vary greatly with parental resources, I examine the probability of giving, and the conditional amount of the gift, by parental asset quartile. I report these results in the bottom panel of Table 4a. For ease of exposition I report only the results for "any event" although the pattern is evident across all events listed in the top panel.[20]

Among children whose parents have assets that place them in the top quartile of the distribution, 26% of those who experience an event receive a transfer and the conditional mean of the amount is $10,500. However, children in this quartile who do not experience any of the events still have a probability of receiving a transfer of 21% and a mean amount of $8800. These figures are much higher than those for children in the next highest asset quartile, even those children who experience a milestone event. This pattern holds across all quartiles: both the probability of receiving a transfer and the amount is greater for those in a higher asset category relative to the categories below them, even if they do not experience an event. Yet within each quartile, those experiencing a milestone have a greater probability of receiving a transfer and conditional on receipt, receive a larger amount. These results demonstrate that the situations of both the parent and the child are important in determining transfers.

One might also wonder whether the gender of the child plays a role in determining the likelihood and/or amount of a transfers. Women are more likely to attend college than are men (c.f. National Center for Education Statistics, 2015) so schooling-related transfers might differ. Similarly, women typically have lower wages than men, weaker attachments to the labor force, and are more likely to be secondary workers. Thus, the responsiveness of parental transfers to the loss of a job or divorce might differ by the gender of the child. In fact, the loss of a job is associated with a decline in family income of $13,565 for sons, and just $3625 for daughters. Conversely, the end of a marriage is associated with a decline of $12,387 for sons but $21,642 for daughters.

Given these differences, I therefore repeat Table 4a with the statistics calculated separately for daughters and sons (Table 4b). As is readily apparent, daughters are more likely to receive transfers than are sons. The probability of receipt is higher in each cell of the table. Both daughters who experienced the event and those who did not have a higher probability of transfer receipt than sons

[18] The $6800 decline in income associated with a job loss is measured as the difference between the change in family income for those with a job loss and the change in family income for those who do not appear to lose a job. Similar numbers for other transitions are calculated in the same manner.

[19] Because the children are relatively young, I refer to this event as a divorce although it could result from the death of a spouse.

[20] Because many parents are retired for at least a portion of the observation period, assets are a better measure of resources than is current income.

Table 4a
Relationship between transfers and life course events.

		Experienced event			Did not experience event		
			Amount >0			Amount >0	
	Average change income[a]	% received transfer	Mean	(Std err)	% received transfer	Mean	(Std err)
Event							
16 years of school (n = 712)	2951	20.2	7104	(941)	13.3	6707	(149)
Married (n = 4198)	15,076	16.8	6908	(411)	13.2	6712	(156)
Bought a home (n = 5202)	7806	16.5	7232	(460)	13.7	6402	(156)
Had a child (n = 19,369)	3417	14.5	7275	(259)	13.4	6745	(158)
Lost job (n = 4011)	−6795	17.5	7454	(583)	13.9	6650	(157)
Marriage ended (n = 3335)	−17,192	21.0	6775	(524)	13.1	6722	(154)
Lost home (n = 3172)	−8728	15.2	6917	(664)	13.9	6461	(151)
Any event (n = 32,299)	−1427	15.6	7252	(195)	13.4	6277	(191)
Any event, by asset quartile							
Lowest quartile (n = 8622)	−2928	7.1	4599	(391)	6.5	3148	(264)
Second asset quartile (n = 8847)	89	12.9	4779	(325)	10.2	3968	(208)
Third asset quartile (n = 7840)	−3329	18.5	6242	(242)	14.3	5112	(311)
Highest (n = 6927)	−404	26.2	10,520	(432)	21.1	8820	(375)

Variables are defined as changes in status between two surveys. Married means that the child was reported as unmarried in one wave and married in the next. Marriage ended is the reverse; the child was married in one wave and not in the next. Bought/lost a home and lost job are measured similarly.
[a] Average change in family income is the difference in income across the two waves for those who experienced the event relative to those children who did not.

Table 4b
Relationship between transfers and life course events.

		Experienced event			Did not experience event		
			Amount>0			Amount>0	
Event	Average change in income[a]	% received transfer	Mean	(Std err)	% received transfer	Mean	(Std err)
Daughters							
Attained 16 years school (n = 414)	3590	21.0	7087	(1305)	14.1	6692	(215)
Married (n = 2012)	17,441	18.1	6836	(577)	14.0	6704	(224)
Bought a home (n = 2601)	8977	17.0	8100	(816)	14.4	6239	(209)
Had a child (n = 9256)	3552	15.2	7504	(425)	14.1	6671	(221)
Lost job (n = 2624)	−3625	17.6	8140	(828)	14.9	6429	(215)
Marriage ended (n = 1713)	−21,642	23.5	6758	(743)	13.8	6709	(222)
Lost home (n = 1585)	−8866	16.5	6132	(806)	14.5	6448	(213)
Any event (n = 16,225)	−1342	16.4	7560	(310)	14.1	5776	(225)
Sons							
Attained 16 years school (n = 298)	2004	19.1	7130	(1315)	12.5	6723	(205)
Married (n = 2186)	12,805	15.7	6984	(586)	12.4	6723	(214)
Bought a home (n = 2601)	6617	16.0	7612	(460)	13.0	6580	(233)
Had a child (n = 10,113)	3281	13.8	7044	(293)	12.6	6829	(226)
Lost job (n = 1387)	−13,565	17.3	6137	(600)	13.0	6867	(224)
Marriage ended (n = 1622)	−12,387	18.4	6798	(714)	12.4	6737	(212)
Lost home (n = 1587)	−8584	13.8	7847	(1090)	13.2	6475	(216)
Any event (n = 16,074)	−1489	14.7	6907	(225)	12.8	6959	(307)

Variables are defined as changes in status between two surveys. Married means that the child was reported as unmarried in one wave and married in the next. Marriage ended is the reverse; the child was married in one wave and in the next. Bought/lost a home and lost job are measured similarly.
[a] Average change in family income is the difference in income across the two waves for those who experienced the event relative to those children who did not.

in the same category. The difference in the probability of receipt is largest for children who have had a marriage end (likely in divorce) with 23.5% of daughters who divorced receiving a transfer compared to just 18.4% of sons. The amounts received, however, are nearly identical: $6758 for daughters and $6798 for sons. Divorce is associated with the highest probability of a transfer for daughters, but not for sons. For sons, transfers are most likely associated with college graduation; 19% of those graduating received a transfer. (For daughters this is the second most common transfer-event, with 21% receiving a transfer.) The amounts received by sons at the completion of 16 years of schooling, $7130, and by daughters, $7087, are not statistically different from each other.

The importance of transfers in response to these various events suggests that it is not just the permanent income that matters as in the standard cross-sectional models; children who experience any of these life course events associated with changes in their financial or life circumstances are more likely to receive a transfer than those who do not. And these transfers likely serve not just to bolster a child's financial resources as predicted by the altruism model, but to mark specific events as well. For example, getting married is associated with a positive shock to lifetime income, yet it is also correlated with a high probability of receiving a transfer, suggesting symbolism or some other motivation may play a role in giving.

What do these patterns mean for differences across siblings? Previous work (McGarry and Schoeni, 1995) has shown that parents rarely report equal transfer amounts to their children in a given survey wave. As demonstrated in that paper, even among those families with just two children, only 14% of parents transferring a positive amount to at least one child, transferred an equal amount to both children. For larger families the fraction giving equal amounts to all children in a single wave approaches zero. Given the variability exhibited from year to year in transfer receipt and expected differences in the timing at which children reach the various milestones noted in Tables 4a and 4b, it is possible that cross-sectional patterns

obscure more equal transfers made over a lifetime. In Table 5, I examine aggregate giving over a 17 year period. The column headings denote the number of children in the family and the first row reports the number of families of that size. I focus on equal giving among those who made at least one transfer over the 17 year period and the second row reports the percent of the total number of families that did so for each family size. There is a slight decline in the likelihood of *any* transfer being made as family size increases, consistent with differences in parental resources, but the trend is not monotonic.

The first panel shows the results for transfers in a single survey period, with all nine biennial reports stacked together. The results are similar to those in other work (e.g. Dunn and Phillips, 1997, McGarry and Schoeni, 1995) which were based on one year of giving, and show that among two child families, just 16% of those making a transfer in a given year transferred the same amount to both children. This figure falls with family size although not monotonically so. When a more generous definition of equality is used, treating as equal those transfers within 10% of the mean amount for the family, the percent making equal gifts is greater, but not by much: 17% of two child families and 6.0% of three child families make "equal" transfers. With a definition of equality of 20% around the mean, the numbers rise further, to 20 and 6.2% for two and three children families, but the majority are treating children *very* differently.

In the second panel, I examine the extent to which the total amount transferred tends to equalize across children over time. Contrary to the assumption that transfers even out over a lifetime, if anything, the reverse appears to be true. While 16% of two child parents, and 4.4% of three child parents who made a transfer, transferred the same amount to each child in a single period, only 5% and 1.1% respectively made equal transfers over the entire window of observation. As shown in the next row, the percentage making equal aggregate transfers rises with a more relaxed definition of equality, but equal giving (or anything close to it) is rare, even over this extended period.

One difficulty with aggregating transfers over a long period of time is that parents typically report giving round amounts such as $1000. Using transfers measured in real dollars will treat as unequal $1000 gifts made to each child in different years. The third panel thus repeats this exercise using nominal dollars. The percent making equal transfers is only slightly higher than that in the second panel, but the implication is the same—parents treat children very differently with respect to the value of transfers, and the distribution is actually *more* unequal when transfers are observed over an extended period of time.

While the probability of equal transfers declines with a longer period of time, it is not obvious that differences in amounts received by siblings becomes larger with the aggregation. To examine the dispersion in amounts over time, in the final two rows of the table, I look at the mean absolute deviation from the family mean, by family size. I do so first for transfers in the first year and then for transfers aggregated across the entire period. In both cases the mean absolute deviation increases with family size up to families of four children and then declines slightly. However, the difference in amounts when aggregated over the sample period is several times larger than that for the first period, indicating that not only does the likelihood of equal transfers diminish, but the dispersion in amounts received by children, increases.

As an additional test of this result, I calculate the deviation from the mean of family transfers over increasing levels of aggregation: in the first period (as shown in the table), then for the mean of cumulative transfers over the first two periods, then for three periods, and so on, for the full window of observation. In results not shown, the mean, median, and standard deviation of these measures all increase monotonically with the amount of time covered. As a more formal test, I also regress the absolute value of the deviation from the family mean for each of these levels of aggregation, for each child, against the number of the number periods used in the calculations (1, 2, 3, …9). In this regression, $\alpha + \beta * years$, the estimate of β is positive and significantly different from zero at a one percent level—a result which holds whether or not I control for the number of children in the family.

The results of Tables 4a and 4b, coupled with the inequality in giving evidenced here in Table 5, suggest that the variation in the timing of life course events could be responsible for a portion of the variation in giving. Indeed, if I regress an indicator variable for whether the family makes equal transfers among siblings on a variable indicating the number of events in the family, I find that the more events experienced by siblings, the more likely the parents are to make unequal gifts. Each additional life course event decreases the probability of equal transfers by 8 percentage points.

The evidence presented here on aggregate giving is the first I know of demonstrating how parents divide transfers among siblings over a lifetime (or significant portion thereof). The results point to a substantial amount of period to period variation in recipiency and suggest that transitory shocks and milestone events likely play important roles in explaining observed behavior. However, if children simply differed in the *timing* of transfer receipt, we would expect greater equality when looking over a longer time horizon than in a single period, contrary to what is observed. I thus turn to regression analysis wherein I can control for permanent differences across children, differences in permanent income, or ability, for example.

5. Regression analysis

To examine more closely the relationship between a child's income and the receipt of transfers, as well as the relative roles played by the milestone events noted in the previous section, I turn to a regression framework where I can control for the observable characteristics of the child and parent. However, also likely to be important are *unobservable* characteristics such as permanent income, industriousness, or ability. To control for these important features I estimate models with both family and child fixed effects.

The simply empirical model is written as $T_{ift} = X_{ift}\beta + \epsilon_{ift}$ where X_{ift} includes observable characteristics of the child (i) and the parent (f), which may or may not vary over time t, and ϵ_{ift} is the error term. In the family fixed effects analysis ϵ_{ift} is written as $\eta_f + u_{ift}$ where η_f represents unobserved characteristics specific to the family. Similarly, in the child fixed effects analysis, the error term is $\alpha_i + e_{ift}$.

In addition to the child's income, the specifications control for the child's age, years of schooling, number of own children, and 0/1 indicator variables for whether the child is male, currently enrolled in school, or married. Gender is fixed over time but the other measures vary between surveys. I also control for characteristics of the parent(s): age, years of schooling, income, assets, and indicators for whether the parent is nonwhite, Hispanic, or in poor health.[21]

5.1. OLS estimates

To estimate the correlates of the probability a child receives a transfer and the amount, I first estimate a pair of simple OLS equations.[22] These specifications offer a description of transfer behavior and provide a base against which to compare later models that control for unobserved heterogeneity. Similar cross-section

[21] Here the child's income is measured using the single CPS imputed amount but the results are similar with the categorical measures. Race, ethnicity, and schooling measures are those for the father, if he is alive, or the mother if not.

[22] Observations for all waves are stacked and the standard errors clustered at the family level. I report estimates from a linear probability model for the receipt of transfers for ease of interpretation, but logit and fixed-effect (conditional) logit specifications yield identical conclusions.

Table 5
Equality of transfers by the number of children (conditional on at least one transfer).

	Number of children in sample			
Measure of parental transfer	2	3	4	5 +
Number of observations	1000	714	488	254
Pct of families making a transfer at least once	74.7	78.2	70.1	65.1
Single year transfers (average of 9 reports):				
Exactly equal	15.9	4.4	1.7	4.9
Within 10% of mean	17.0	6.0	5.4	4.9
Within 20% of mean	19.7	6.2	5.6	5.0
Aggregated 1992–2008 real dollars:				
Exactly equal	5.0	1.1	1.2	1.7
Within 10% of mean	14.2	2.3	1.5	1.7
Within 20% of mean	22.9	4.3	2.3	2.3
Aggregated 1992–2008 nominal dollars:				
Exactly equal	6.0	1.4	1.2	1.7
Within 10% of mean	15.3	2.2	1.5	1.7
Within 20% of mean	23.2	3.7	2.3	2.3
Mean deviation from family mean (absolute value)				
Year one (in dollars)	325	724	1239	1096
Aggregated 1992–2008 (in dollars)	2074	4338	6524	5014

Notes: Families are grouped by the number of children in the sample, not necessarily the number in the family. Children are missing from the sample if they were not at least 18 years old, living away from home in 1992 (excluding those temporarily away for school), and observed in all waves of the survey.

Table 6
Effects of child's characteristics on the probability and amount of a transfer (n=67,523).

	OLS		Family F.E.		Child F.E.	
	(1) Prob	(2) Amount	(3) Prob	(4) Amount	(5) Prob	(6) Amount
Child variables:						
Income ($10,000s)	−0.013***	−61.2***	−0.014***	−64.0***	−0.009***	−39.4***
	(0.001)	(22.4)	(0.001)	(10.1)	(0.001)	(11.7)
Age	−0.004***	−37.4***	−0.004***	−33.1***	−0.007*	−81.5
	(0.000)	(5.5)	(0.000)	(6.48)	(0.004)	(76.3)
Years of schooling	0.003***	26.7	−0.001	−25.8	−0.002	−10.6
	(0.001)	(21.1)	(0.001)	(16.6)	(0.002)	(35.1)
Married	−0.028***	−217***	−0.028***	−166.6***	−0.034***	−189**
	(0.004)	(66.2)	(0.003)	(62.3)	(0.004)	(79.8)
Own home	−0.023***	−28.3	−0.018***	−20.6	−0.007*	69.0
	(0.004)	(63.5)	(0.003)	(60.7)	(0.004)	(74.5)
Currently in school	0.079***	807***	0.060***	793***	0.060***	751***
	(0.009)	(155)	(0.006)	(114)	(0.007)	(129)
Number of children	0.010***	27.7	0.010***	50.5**	−0.001	−28.1
	(0.001)	(18.6)	(0.001)	(20.0)	(0.002)	(32.5)
Male	−0.011***	−30.6	−0.017***	−85.5		
	(0.004)	(60.6)	(0.003)	(54.4)		
Nonwhite	−0.018***	−143**				
	(0.005)	(57.3)				
Number of siblings	−0.020***	−134.3***				
	(0.001)	(16.3)				
Mean dependent variable	0.139	966	0.139	966	0.139	966
R2	0.089	0.046	0.30	0.20	0.39	0.27

Standard errors are in parentheses. OLS regressions also include a dummy variable denoting that the parent could not report the child's income, dummy variables for each survey year, and the following characteristics of the parents: head's age, marital status, education, ethnicity, income, wealth, either parent in poor health, and number of children.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

results, using one or two years of data, have been reported elsewhere (McGarry and Schoeni, 1995) so I do not discuss them in detail.

In the first pair of columns in Table 6 there is a strong negative relationship between the child's income and both the probability of receiving a transfer and the amount. Note, however, that the effects of income are small in monetary terms. A $10,000 increase in the child's income is associated with a 1.3 percentage point decline in the probability of receiving a transfer and just a $61 decline in the amount. Older children and married children are less likely to receive a transfer and receive less, perhaps attesting to their greater maturity or financial stability, as well as the availability of a spouse to help smooth negative income shocks. Children who are enrolled in college are more likely to receive a transfer and receive significantly more than those who are not. Sons are less likely to receive a transfer than are daughters but there is no difference in the amounts by gender. Children in non-white families also get less, even controlling for

parental income, wealth, and schooling, and each additional sibling significantly reduces the probability of a transfer (by 2 percentage points) and the amount, by $134. Each sibling is thus equivalent to approximately a $20,000 rise in family income, an effect larger in absolute value than the positive effect of having an additional child.

Unsurprisingly, there is a strong positive relationship between parental resources and transfers; the greater the parent's income, assets, and education level, the more likely the child is to receive a transfer and the greater the amount (not shown). The variable indicating that a parent (or either parent) is in poor health has a small negative effect (significant at the 10% level) in the equation for the probability of a transfer but is not significant in the equation for the amount.

5.2. Family fixed effects

The second pair of columns reports the estimates for the family fixed effects specifications. The unobserved family component captures differences in generosity, or perhaps dynastic wealth across families.

Perhaps surprisingly, most of the coefficients for the family fixed effects models are similar to the first set of estimates. The effect of a child's income is similar in magnitude and the only notable change is with respect to years of schooling. In the OLS specification there is a positive and significant relationship between years of completed schooling and the likelihood of a transfer and a positive (although not significantly different from zero, $p = 0.14$) relationship with the amount of the transfer. However, in the family fixed effects estimation, the coefficient estimates for schooling are negative but not significantly different from zero in either regression. Taken together the results indicate that children with higher levels of schooling are more likely to live in families that made transfers, suggesting perhaps that parents who give generously for schooling, allowing their children to complete more years of education, continue to give once the children have completed school. When controlling for this family fixed effect there is no difference in giving as a function of years of schooling.

5.3. Child fixed effects

The simple altruistic model predicts that parents will choose the amount to transfer over a lifetime with regard to a child's permanent income. However, if a child is unable to borrow freely across periods parents may make transfers to alleviate liquidity constraints as well. Thus transfers will be made with regard to both permanent and current incomes. The empirical specifications above do not contain a measure of permanent income of the child beyond the inclusion of completed schooling. To control for this and other fixed characteristics of the child, I estimate a child fixed effects model. Because I also control for schooling in the regression, the individual-specific error might best be thought of as permanent income less the effect of schooling (and other observables). If one considers permanent income to be primarily a function of schooling and ability, this unobserved error component can be termed a measure of ability.

The estimated coefficients from this specification are shown in the right-most pair of columns in Table 6. When child fixed effects are controlled for there continues to be a significant negative relationship between a child's income and both the probability of transfer receipt and the amount, but the effect is dampened somewhat from the OLS version. The decline is approximately 30% for the probability and a similar 35% for the amount. If we consider the unobserved child effect to be ability, then this result suggests that, all else constant, more able children receive less generous transfers than less able. Or conversely, ceteris paribus, parents provide more support to less able children, a result that accords with our intuition.

5.3.1. Life course events

The results from Table 6 demonstrate that transfers respond to changes in a child's income and are decidedly compensatory. In addition to income, measures such as age and marital status that likely attest to a higher degree of maturity and/or a lower probability of liquidity constraints, are negatively related to transfers. Examining the effect of current income, less other components, is an important contribution of the paper and the results indicate that short-term fluctuations in income as well as permanent differences are important determinants of transfers.

However, other events in a child's life may lead to changes in the expectation of permanent income or to liquidity constraints, or may simply warrant giving in its own right. Table 7a re-examines the probability and amount of a transfer as functions of those variables included in Table 6 as well as indicators for the various events examined in Tables 4a and 4b, the end of a marriage, a new baby, a job loss, etc. The sample size here is smaller than in table 6 because the events are defined as current status relative to that in the previous wave so there are no such measures in the first wave of data.

Even with the numerous controls for parental resources and for other characteristics of the child, these life cycle events by and large are significant predictors of transfers. In both the equations for probabilities and those for the amounts, and across specifications, the magnitudes of the effects are larger than those of the other characteristics of the child. The estimated effect of a divorce in the OLS regression, 5.8 percentage points on the probability of a transfer, is similar to a decline of $40,000 in income. For the amount, the increase associated with a divorce is $379, similar to the effect of a decline of nearly $100,000 in income. Similarly large effects are found for the loss of a job. In terms of happier events, a new home, completion of college, or getting married, also have large effects.

Interestingly, the magnitude of the other variables in the regression are relatively unchanged when these event measures are included. And, as seen in Table 6, there is little change in the coefficients of interest when moving from OLS to family fixed effects to child fixed effects.

In the OLS regressions in Tables 6 and 7a, the number of siblings has a significantly negative effect on both the probability and magnitude of transfers as siblings represent competition for the limited resources of the parents. Given this relationship, the occurrence of life course events for siblings may likewise dampen transfer receipt. Alternatively, if parents endeavor to treat children equally with regard to transfers in a given period, the occurrence of an event for one child may increase transfers to his siblings. I repeated the regressions in Table 7a including various measures of the experiences of siblings. I used, in turn, the number of siblings experiencing at least one of these events, the fraction experiencing at least one event, and whether any sibling experienced each of these events in a particular period. For parsimony I report only the results with an aggregate measure of any event for a sibling (Table 7b). As shown, the coefficient for "any sibling event" is negative and significantly different from zero at the one percent level for the probability of a transfer, and negative and significantly different from zero at a 10% level for the amount. The advent of a life course event for a sibling decreases the probability of receiving a transfer by 1.1 percentage points, far smaller than the positive effect of the occurrence of an event to oneself and about one-half the magnitude of the existence of an additional sibling. However, the effects are not economically or statistically significant in fixed effects specifications.

5.4. Living arrangements

In addition to cash transfers, a parent can provide assistance to a child by inviting a child to share a family home. My sample consists of children who at one point lived independently, so sharing a home with a parent would involve the fixed cost of moving, perhaps storing

Table 7a
Effects of child's characteristics on the probability and amount of a transfer (n=41,993).

	OLS		Family F.E.		Child F.E.	
	(1) Prob	(2) Amount	(3) Prob	(4) Amount	(5) Prob	(6) Amount
Child variables:						
Income ($10,000s)	−0.013***	−40.4*	−0.014***	−43.5***	−0.008***	3.15
	(0.001)	(28.6)	(0.001)	(11.6)	(0.001)	(14.2)
Age	−0.004***	−24.23***	−0.004***	−31.3***	−0.004	−162.0
	(0.00)	(7.2)	(0.000)	(7.64)	(0.015)	(262.6)
Years of schooling	0.002**	10.9	−0.002**	−22.2	0.001	−7.4
	(0.001)	(25.1)	(0.001)	(19.6)	(0.002)	(46.9)
Married	−0.022***	−269***	−0.019***	−210.8***	−0.031***	−315.2**
	(0.006)	(90.5)	(0.005)	(81.7)	(0.007)	(125.4)
Own home	−0.038***	−110.2	−0.033***	−120.6	−0.018***	−55.1
	(0.006)	(90.2)	(0.005)	(80.8)	(0.007)	(116.5)
Currently in school	0.060***	492.9***	0.045***	414.6***	0.047***	375.4***
	(0.011)	(143)	(0.008)	(133)	(0.009)	(161.2)
Number of children	0.013***	73.7***	0.013***	103.2***	0.001	16.3
	(0.002)	(22.7)	(0.001)	(25.4)	(0.003)	(47.8)
Male	−0.012***	−3.9	−0.017***	−46.8		
	(0.004)	(64.6)	(0.0043)	(63.1)		
Nonwhite	−0.011***	−61.6				
	(0.006)	(73.0)				
Siblings	−0.021***	−117.8***				
	(0.001)	(19.0)				
Events:						
Newly divorced	0.058***	378.0***	0.057***	378.1***	0.052***	332.2**
	(0.010)	(145.3)	(0.008)	(138.1)	(0.009)	(160.0)
Lost job	0.032***	448.7***	0.027***	337.3***	0.029***	355.1***
	(0.007)	(145.5)	(0.007)	(111.7)	(0.007)	(129.8)
Lost home	−0.017**	134.0	−0.015**	92.5	−0.011	116.1
	(0.008)	(131.3)	(0.008)	(132.4)	(0.009)	(153.9)
New grad	0.051**	983.7**	0.064***	955.5***	0.067***	1086.7***
	(0.023)	(436.8)	(0.018)	(306.4)	(0.019)	(337.4)
New married	0.025***	271.0**	0.022***	238.4**	0.024***	270.8**
	(0.008)	(109.3)	(0.007)	(114.0)	(0.007)	(131.7)
New home	0.048***	449.7***	0.041***	340.7***	0.037***	317.2***
	(0.006)	(122.9)	(0.006)	(96.3)	(0.006)	(110.2)
New grandchild	0.000	−33.1	−0.002	−5.1	0.003	71.3
	(0.001)	(94.2)	(0.005)	(84.1)	(0.006)	(96.9)
Mean dependent variable	0.145	964	0.145	964	0.145	964
R2	0.095	0.069	0.30	0.28	0.463	0.370

Standard errors are in parentheses. OLS regressions also include a dummy variable denoting that the parent could not report the child's income, dummy variables for each survey year, and the following characteristics of the parents: head's age, marital status, education, ethnicity, income, wealth, either parent in poor health, and number of children.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

furniture, a change in commuting patterns if a child has a job, and so forth. It also likely involves a loss of privacy for both parties. In many ways then it is a larger commitment to assisting the child than providing a cash transfer.

Although likely financially important, it is difficult to quantify the degree of assistance provided by coresidence. In particular, it is not always clear who is helped by the arrangement (the parent or the child). However, given the relatively young age of the parents in the sample, one might speculate that few are yet to need care.[23] It is also not clear whether the child is reimbursing the parent somehow or how one might construct an imputed rental value.[24]

Despite these difficulties, in Table 8, I examine the relationship between child characteristics and coresidence measured as a 0/1 variable using the child fixed effects specification. The first column provides the results for a specification with coresidence on the left hand side and the second uses any transfer, either coresidence or cash, as the dependent variable.

Unsurprisingly, the child's income is again a highly significant predictor of assistance; low income children are far more likely to coreside than children with high incomes but the effects are small in magnitude although large relative to the probability of coresiding. The average probability of coresidence is two percent, so a change of $10,000 in the child's income is associated with a change of 0.3 percentage points or 15%. Married children and children who own a home are less likely to coreside, while the reverse is true for those children who are enrolled in school. Not shown in the tables is the effect of parental resources. While parental income and wealth have strong positive effects on giving, their effects on coresidence, while positive, are not significantly different from zero.

In terms of events in the child's life, we again see a strong relationship between divorce and unemployment and likely help from a parent. Children experiencing either of these events since the previous interview are significantly more likely to be living with a parent. The loss of a job increases the probability of coresidence by 1.2 percentage points. Recall that the mean probability of coresidence is just two percent, so this increase is quite large in percentage terms. Similarly, the effect of a divorce on the probability of living together, 0.9

[23] If I include a dummy variable indicating that the child is providing care to the parent, the variable is not significantly different from zero. See Wiemers et al. (forthcoming) for a discussion of family living arrangements and assistance over the life course.
[24] See Kaplan (2012) for a discussion of the use of coresidence as insurance against negative shocks to income.

Table 7b
Effects of child's characteristics on the probability and amount of a transfer (n=41,993).

	OLS		Family F.E.		Child F.E.	
	(1) Prob	(2) Amount	(3) Prob	(4) Amount	(5) Prob	(6) Amount
Child variables:						
Income ($10,000s)	−0.013***	−40.4**	−0.014***	−43.5***	−0.008***	3.12
	(0.001)	(28.6)	(0.001)	(11.6)	(0.001)	(14.2)
Age	−0.004***	−25.0***	−0.004***	−31.3***	−0.004	−160.8
	(0.000)	(6.7)	(0.000)	(7.65)	(0.015)	(262.7)
Years of schooling	0.002*	10.7	−0.002**	−21.2	0.001	−7.5
	(0.001)	(17.4)	(0.001)	(19.6)	(0.002)	(47.9)
Married	−0.022***	−270.6***	−0.019***	−210.8***	−0.031***	−315.1**
	(0.006)	(77.9)	(0.005)	(81.7)	(0.007)	(125.4)
Own home	−0.038***	−111.4	−0.033***	−126.6	−0.018***	−55.0
	(0.006)	(77.1)	(0.005)	(80.8)	(0.007)	(116.5)
Currently in school	0.060***	493.0***	0.045***	414.6***	0.047***	375.3**
	(0.011)	(144.2)	(0.008)	(146)	(0.009)	(161.3)
Number of children	0.013***	74.2***	0.013***	103.1***	0.001	16.4
	(0.002)	(22.8)	(0.001)	(25.4)	(0.003)	(47.9)
Male	−0.012***	−5.3	−0.017***	−46.8		
	(0.004)	(65.0)	(0.004)	(63.1)		
Nonwhite	−0.012**	−64.0				
	(0.006)	(55.2)				
Siblings	−0.020***	−108.9***				
	(0.001)	(12.4)				
Events:						
Newly divorced	0.058***	378.7***	0.057***	378.0***	0.052***	332.1**
	(0.010)	(139.5)	(0.008)	(138.1)	(0.009)	(160.0)
Lost job	0.032***	450.9***	0.027***	337.2***	0.029***	354.8***
	(0.008)	(126.9)	(0.007)	(111.7)	(0.007)	(129.8)
Lost home	−0.017**	139.7	−0.015**	92.5	−0.011	115.4
	(0.009)	(133.9)	(0.008)	(132.4)	(0.009)	(153.9)
New grad	0.052**	987.8**	0.064***	955.4***	0.067***	1086.5***
	(0.024)	(430.5)	(0.018)	(306.4)	(0.019)	(337.4)
New married	0.025***	272.9**	0.022***	238.3**	0.024***	270.8**
	(0.008)	(110.6)	(0.007)	(114.0)	(0.007)	(131.7)
New home	0.048***	453.8***	0.041***	340.7***	0.037***	316.6***
	(0.007)	(118.3)	(0.006)	(96.3)	(0.006)	(110.2)
New grandchild	0.000	−29.1	−0.002	−15.1	0.003	70.7
	(0.005)	(93.5)	(0.005)	(84.1)	(0.006)	(97.0)
Any sibling event	−0.011**	−112.5*	0.000	−1.7	0.003	16.5
	(0.005)	(62.9)	(0.004)	(63.6)	(0.004)	(68.9)
Mean dependent variable	0.145	964	0.145	964	0.145	964
R2	0.095	0.069	0.33	0.28	0.463	0.370

Standard errors are in parentheses. OLS regressions also include a dummy variable denoting that the parent could not report the child's income, dummy variables for each survey year, and the following characteristics of the parents: head's age, marital status, education, ethnicity, income, wealth, either parent in poor health, and number of children.
*** $p < 0.01$.
** $p < 0.05$
* $p < 0.1$.

percentage points, is large and significantly different from zero at the one percent level.

When coresidence is combined with cash gifts to create an expanded measure of potential support, the results are quite similar to the regression results for cash gifts alone given the small incidence of coresidence. The small number of families that coreside, do not alter the effects of any of the coefficients.

6. Discussion and conclusions

Understanding intergenerational transfers is particularly important when examining the distribution of the benefits and burdens of public transfers, the persistence of inequality across generations, and the ability of individuals and families to smooth consumption. This paper considers parental transfers in a new light by focusing on the dynamic aspects of giving to children, providing some of the first evidence of important time varying aspects of transfer behavior. Using panel data, I find a large amount of variation over time and within families in both the probability a child receives a transfer and in the amount received. The results presented here suggest that a substantial fraction of transfers are made in response to short-term income fluctuations, consistent with the liquidity constraint argument of Cox (1990). The importance of a child's need is further evidenced by the results of a regression analysis. Using multiple observations per child I am able to control for unobserved fixed child specific characteristics such as ability or permanent income. I find that the estimated effect of the child's current income on transfers is biased upward when permanent differences are ignored. However, even when fixed characteristics are controlled for, there continues to be a significant negative relationship between current income and transfers, pointing to the compensatory nature of such behavior and the potential role of transfers in smoothing consumption. Nonetheless, despite the consistent patterns, the magnitude of the income effect is small, with parents making up only pennies on the dollar. Thus, while compensatory transfers can mitigate differences in resources across siblings, they do not eliminate any such differences.

I also directly examine the coincidence of transfers with life course events. I find substantial giving particularly for events that are associated with negative shocks to income, on average, such as

Table 8
Effects of child's characteristics on the probability of coresidence or cash transfer.

	Child fixed effects models	
	Coresidence	Coresidence or cash transfer
Child variables:		
Income ($10,000s)	−0.003***	−0.010***
	(0.000)	(0.000)
Age	0.003	−0.001
	(0.006)	(0.015)
Years of schooling	−0.002	−0.000
	(0.001)	(0.003)
Married	−0.027***	−0.051***
	(0.003)	(0.007)
Own home	−0.019***	−0.032***
	(0.003)	(0.007)
Currently in school	0.006***	0.051***
	(0.004)	(0.009)
Number of children	−0.001	0.000
	(0.001)	(0.003)
Child provides care		
Events:		
Newly divorced	0.009***	0.039***
	(0.004)	(0.010)
Lost job	0.012***	0.034***
	(0.003)	(0.008)
Lost home	−0.001	−0.008
	(0.004)	(0.009)
New grad	0.001	0.077***
	(0.002)	(0.020)
New married	−0.005*	0.021***
	(0.003)	(0.008)
New home	0.005**	0.040***
	(0.002)	(0.006)
New grandchild	−0.008	0.004
	(0.002)	(0.006)
Mean dependent variable	0.02	0.160
R2	0.50	0.47

Standard errors arein parentheses. OLS regressions also include a dummy variable denoting that the parent could not report the child's income, dummy variables for each survey year, and the following characteristics of the parents: head's age, marital status, education, ethnicity, income, wealth, either parent in poor health, and number of children.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

a divorce or loss of a job, further confirming the role of parents as helping to smooth consumption when times are difficult. However, transfers are made for positive as well as negative events with significantly larger transfers made to those who marry, have a child, or complete four years of college relative to those who do not experience a life course event. The effects of these events on giving are large relative to the effects of current income and suggest that parents are often motivated to give by particular shocks to a child's income.

Given the importance of transfers targeting specific events in a child's life, and the variation across siblings in the timing of when events such as marriage, the birth of a child, or unemployment occur, the finding that children received differing amounts of transfers at a point in time is not surprising. However, I find no evidence that inequality in the amount received across siblings is reduced when transfers are aggregated over an extended period—in fact, when transfers are aggregated over the 17 years of data in my sample, the totals given appear to be *more* unequal than are transfers made in a given year. Thus, parents do not appear to equalize transfers across children over time. This result adds further evidence to the well-known puzzle in the literature regarding the vastly different patterns of giving for inter vivos transfers and bequests wherein estates are nearly uniformly divided equally across children. The results presented here rule out the oft speculated notion that a longer timeframe would yield more equality across siblings in inter vivos transfers than is seen in cross section, and suggest that the difference in behavior for the two types of transfers may be even more stark than previously thought. Such differences in behavior suggest differing motives for the distribution of inter vivos transfers and bequests (Bernheim and Severinov, 2003, Wilhelm, 1996). The varying patterns also suggest that the even with data on a lifetime of parental giving (including bequests), siblings will typically have received very different amounts from their parents.

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