THE PATTERNS OF PARENTAL INTERVIVOS TRANSFERS TO ADULT CHILDREN

Siqiang Yang* and Marla Ripoll†

May, 2022

Abstract

This paper documents the patterns of total intervivos transfers adult children receive from their parents in the United States. Using 1996-2014 panel data from the Health and Retirement Study, our paper departs from the literature by following adult children over time and constructing measures of aggregated transfers received over different time horizons. We find that while the probability and transfer amount decrease as the child ages, conditional on receiving the age of the child is uncorrelated with transfer amounts. We characterize this lack of correlation as a result of parents following different transfer strategies, with some giving only early in the period, others giving only late, and others in both. Transfer strategies even vary within families, with some children receiving more generously and more consistently than others, even when controlling for children's income and age. Regarding total transfers over the 20-year sample period, we find that relative to their permanent income, poorer parents transfer more generously than high-income parents. Intervivos transfers are the predominant way in which adult children receive financial support from parents across the income distribution, in contrast with bequests which are received by a small fraction of children with high-income parents.

Key words: parental altruism, timing of intervivos transfers, aggregated intervivos transfers, permanent income, bequests

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 twice as large as the incidence of bequests.[1] Understanding the patterns of parental transfers is important because they play an insurance role and they also constitute a source of wealth accumulation. Most of the available empirical work on parental intervivos transfers has been conducted using cross-sectional data from the Survey of Consumer Finances (Gale and Scholz, 1994) or the Panel Study of Income Dynamics (Altonji *et al.*, 1997). Few exceptions include Hurd *et al.* (2011) and McGarry (2016), who use panel data from the Health and Retirement Study (HRS); and Scholz *et al.* (2014), who use data from the Wisconsin Longitudinal Study. Panel transfer data is unique, not only because it allows to control for unobserved characteristics through child and family fixed effects, but it also makes it possible to construct measures of aggregated

*School of Economics, Nankai University. E-mail: siy10@nankai.edu.cn

†Corresponding author. Department of Economics, University of Pittsburgh. E-mail: ripoll@pitt.edu

[1] Using data from the 1986 Survey of Consumer Finances, Gale and Scholz (1994) document that while 7.1% of parents reported giving major intervivos transfers (of at least $3,000 during the 3-year period 1983-1985) to non-coresident adult children, only 3.7% children received inheritances in 1986. As Gale and Scholz discuss, the incidence of intervivos transfers must be even larger if smaller transfers are included.

transfers over time, which give a more complete picture of total parental support to children over the lifecycle. In fact, as we show, when we follow children over time, the incidence and amount of parental intervivos transfers is even larger than the one documented in Gale and Scholz (1994), and certainly so relative to bequests, which are zero for the majority of adult children in the United States.

The purpose of this paper is to document the patterns of total intervivos transfers in panel data. To the extent of our knowledge, ours is the first analysis of this kind. This analysis brings two types of new insights to the literature on parental transfers. First, there is little knowledge of how sizable total intervivos transfers are, how they compare with bequests, and how they vary across the income distribution and across siblings. Different from bequests, intervivos transfers may occur many times over the whole lifecycle. Panel data provides a unique opportunity to aggregate these transfers over time. Analyzing total intervivos transfers allows for a better understanding of the extent of intergenerational transfers, particularly for the majority of adult children, who generally do not receive bequests. Second, whether parents choose to transfer early to their adult children, front-loading transfers, or if they choose to delay transfers, has been central to theories of dynamic parental altruism. For example, in the case of models of strategic interaction between an altruistic parent and a child (Bruce and Waldman, 1990; Altonji *et al.*, 1997; Chu, 2020; Barczyk and Kredrel, 2021), inefficiencies exist because young adult children may face borrowing constraints, and because selfish kids may follow the strategy of saving less and extracting resources from the altruistic parent in future periods (Samaritan's dilemma). Richer parents may be able to implement what they see as the first best, helping the constrained young adult child in a limited way to avoid that the child overconsumes, and postponing some transfers for later. Parents with less resources may instead front-load transfers, rendering future transfers inoperative (Bruce and Waldman, 1990; Chu, 2020). Using panel data to follow the dynamics of transfers for a parent-kid pair over time allows us to aggregate transfers in early versus late periods, and to examine the types of parents who front-load transfers versus those who delay and those who give both early and late.

We use longitudinal biennial HRS data from 1996 to 2014 (10 waves). Our sample includes 6,444 parent-kid pairs for whom we observe intervivos transfers information (zero or positive) for all waves. Parental intervivos transfers of at least $500 are reported in HRS data separately for each adult child. In addition to transfer data, the HRS includes other economic and demographic information about parents and children. Inspired by theoretical models of parental transfers, we use the HRS data to document a number of relevant empirical patterns. We also analyze a smaller sample of parent-kids pairs for which at least one of the parents dies during the sample period, so that we can compute total intervivos transfers over the 20-year period as well as bequests.

Our analysis yields the following main findings. First, while on average only 14% of children receive transfers in any given HRS wave, when we follow adult children over a 20-year period, 48% receive at least once. The average transfer amount by wave is $975, and the average total amount over 20 years is $9,613. Conditional on receiving, the average transfer by wave is $6,938, while it is $19,936 total over 20 years. Both transfers by wave and total transfers exhibit high dispersion, making inequality a prevalent feature of parental intervivos transfers data.

Second, using transfers by wave, we verify the fact that the probability of receiving and the transfer amount decrease as the adult child ages, a result that has been documented elsewhere (McGarry, 2016). But a novel finding is that conditional on receiving, there is no correlation between age and the transfer amount received. To explore the origin of this finding, we exploit the longitudinal nature of the data to construct measures of total early transfers (first five waves) and total late transfers (last five waves) for each parent-kid pair. We find that even controlling for child's cohort (age bracket in 1996), average total early transfers are larger than late transfers. For example, children on average receive $766 extra in the early period relative to the late period, or $813 once we control for parent-kid fixed effects. Once more, this decreasing pattern of average aggregated transfers mirrors the decreasing probability of receiving over time as adult children age. But when looking only among those who receive positive amounts, this decreasing pattern disappears: conditional on receiving, total early transfer amounts are no different than total late transfers. We find that underlying this pattern there is a variety of transfer types, with some children receiving only early over the 20-year period we observe them, others receiving only late, and others both early and late.

Third, regarding these transfer types, the fraction of children who receive both early and late increases with parental permanent income suggesting that richer parents tend to follow the strategy of giving both early and late as predicted by the theory. For example, relative to children with parents in the first income quartile, children with parents in the second quartile are 1.9 times more likely to receive in both periods when compared with those who only receive early. The corresponding relative risk ratios are 2.6 for children with parents in the third quartile, and 3.0 for those in the fourth quartile. But we also find that regardless of parental income, children who receive both early and late receive more generously in each period than those receiving only early and only late. Specifically, controlling for a number of observables, we find that children who receive in both periods get \$7,488 more in the early period (10 years) than those who only receive early. Using family fixed effects to control for unobservable parental characteristics, this number decreases to \$5,420, still a sizable difference. This suggests that across the income distribution, and even when controlling for children's income and age, parents follow different transferring strategies among siblings, with those who receive more generously in the early period also receiving positive transfers later on.

Fourth, regarding total transfers over the 20-year period, we find that conditional on giving, average total transfers are \$10,940 for children with parents in the lowest income quartile, while they are \$29,523 for the highest quartile. However, poorer parents give a larger share of their permanent income in intervivos transfers than those in the highest quartile: the share is 19.2% for the lowest quartile and 10.4% for the highest. Although some high-income parents may give proportionally less intervivos transfers but give more bequests, the incidence of bequests is small even among parents in the highest income quartile. Using a smaller sample for which parental deaths and bequests are observed, we find that only 7% of children with parents in the highest income quartile receive bequests, while 45% receive positive intervivos transfers. In addition, average (zero and positive) bequests account for about 40% of average parental gifts (total intervivos transfers plus bequests), suggesting that intervivos transfers are the main form of financial support for the typical adult child in the United States.

We also find that total transfers are positively correlated with parental wealth, income, and schooling, as well as with children's schooling. Total transfers are instead negatively correlated with child's income and number of siblings. These correlations are in line with models of parental altruism. The point estimate on number of siblings is particularly sizeable, with every additional sibling reducing total positive transfers by \$2,602. We also find evidence that within families intervivos transfers are compensatory, with lower-income siblings receiving larger transfers at a rate of \$1,873 more of total transfers for every \$10,000 less of average income.

Last, in a novel empirical exercise, we revisit the transfer-income derivative for models of parental altruism using panel data. This derivative measures the change in parental transfers as a result of a redistribution of one-dollar of permanent income from the child to the parent. In an influential paper, Altonji *et al.* (1997) estimated this derivative using cross-sectional data and found a transfer-derivative of much less than one dollar, interpreting this result as a strong rejection of parental altruism. But subsequent work by Chu (2020) and Barczyk and Kredler (2021) demonstrated that the transfer-income derivative in Altonji *et al.* (1997) was misspecified, and that the model of parental altruism is consistent with a derivative of much less than a dollar. This is the case because as a result of redistributing income from child to parent, there can be switches from situations where zero transfers are given, to instances with positive transfers. Using panel data we estimate that a redistribution of one dollar of permanent income from a recipient child to a donor parents leads to an increase of parental transfers of \$0.086 in one wave, but of \$0.25 over 20 years (10 waves). This trifold increase in the transfer-income derivative roughly reflects that conditional on receiving, the average per wave transfer is \$6,938 while the average total is \$19,936. This finding underscores the advantages of panel data, where aggregated transfers can be computed over time.

The most related papers to ours are the few empirical papers using longitudinal parental transfer data (Hurd *et al.*, 2011; Scholz *et al.*, 2014; and McGarry, 2016). As mentioned, relative to these papers, ours contributes to the literature by analyzing the properties of aggregated intervivos transfers at different time horizons over the 20-year period for which we have data. Hurd *et al.* (2011) use HRS data for the period 1992-2006. They use repeated cross-sections to characterize intervivos transfers from the perspective of parents, who are the givers. They examine the amounts parents give in each wave to their children as a whole, regardless of how much each child receives and under what circumstances. Different from their paper, our unit of observation is the parent-kid pair, as we care about how and why individual children receive, and how aggregated transfers to each child at different time horizons behave. As Hurd *et al.* (2011), McGarry (2016) also uses repeated cross-sections from HRS to conduct an empirical analysis of transfers by wave, and to determine how transfers 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. In contrast to her work, here we purely focus on the empirical analysis of aggregated transfers. We also discuss the main insights of dynamic models of parental altruism and use them to interpret our empirical findings.

Scholz *et al.* (2014) use data from the Wisconsin Longitudinal Study to analyze the long-run determinants of intergenerational transfers. A limitation of this data is that information is available only from few waves far apart in time, so the reporting of transfers is based on recalling over a long period of time. On the other hand, this data has observations across three generations, which provides a way to examine the correlation between having received a gift from own parents and the incidence of given to own children. Like Scholz *et al.* (2014), our work also takes a more long-run perspective by aggregating transfers to children over time. Since the HRS has more frequent information over time, we are able to examine whether parents give transfers early or tend to postpone for later. Our work complements Scholz *et al.* (2014).

The remainder of the paper is organized as follows. Section 2 discusses the main insights from dynamic models of parental altruism with particular attention to the timing of transfers. We consider both models with commitment and models with strategic interaction between the parent and child, which developed in parallel. Section 3 presents our main empirical analysis, with a focus on the timing of transfers (early versus late) and the properties of total intervivos transfers. Section 4 extends the empirical analysis by considering bequests and coresidency between adult children and parents, both of which represent other forms of intergenerational transfers. Section 5 concludes.

2 Insights from altruistic theoretical models

Models of parental altruism have been central in understanding parental intervivos transfers.[2] Two parallel strands of this literature developed almost simultaneously, one considering dynastic models of parental altruism with commitment, and the other examining strategic interactions between a parent and a child. The first strand dates as early as Altig and Davis (1989, 1992), who examine

[2] The exchange motive has also been considered in the literature of parental transfers (Cox and Rank, 1992), but the focus of our paper is on the predictions of models with parental altruism.

a deterministic overlapping generations model linked by parental altruism. In this class of models parental transfers primarily occur early in the life cycle, since transfers are linked to binding borrowing constraints for the child. The second strand of the literature goes back to Bruce and Waldman (1990), who analyzed a deterministic two-period strategic game between a parent and a child. Refinements of this model that include borrowing constraints for the child in the first period, and income uncertainty in the second period, were developed subsequently by Altonji *et al.* (1997), Chu (2020) and Barczyk and Kredler (2021), among others. As in dynastic models with commitment, this class of models also links the timing of parental transfers to binding borrowing constraints, but strategic considerations introduce the possibility that an unconstrained child receives a transfer earlier in adult life (Chu, 2020).

In this section we summarize the insights of these two strands of the literature and illustrate how models of parental altruism deliver a rich set of predictions on the patterns of parental inter-vivos transfers. We show that both types of models predict that transfers may occur early in the lifecycle, late, or both. We use these insights in the empirical section to interpret the patterns from longitudinal data.

2.1 Dynastic models with commitment

The timing of parental transfers in dynastic models of altruism was first analyzed in the early 1990s as part of a literature exploring Ricardian equivalence, government debt, and social security in models with intergenerational linkages. Notably, Altig and Davis (1989, 1992) explored this issue in a three-period overlapping generations model with parental altruism and commitment. In their model the timing of parental transfers can be pinned down because there are credit frictions in the form of a wedge between borrowing and lending rates. Their main finding is that when borrowing rates exceed lending rates, then if parental transfers are positive they will occur in the period in which the child faces a binding borrowing constraint, which is when the child is a young adult. More recently, Cordoba and Ripoll (2019) generalize this result in the context of a multi-period model where parents also choose the number of children endogenously. They find that if parental transfers are positive, they will occur in the period in which the child is most constrained over the lifecycle. In addition, family size reduces both the probability that parental transfers will occur, as well as the amount.

To highlight the intuition of these results, consider the following dynastic model. Relative to Altig and Davis (1989, 1992), an innovation of our model is that it includes the cases in which transfers occur early in the lifecycle, late, or both. Consider the case of an altruistic adult parent in an overlapping generations setting. Adult life lasts for four periods indexed by t. For simplicity assume that all children are born at the same time and that there is a gap of one period between each kid and the parent, so that parent and adult children overlap three periods. This is the simplest model in which we can examine the timing of parental transfers in the presence of a realistic hump-shaped income profile, credit constraints and multiple children.

The parent head of dynasty solves the following problem

$$V = \max_{[c_t, a_{t+1}, b_t^k]} \sum\nolimits_{t=1}^{4} \beta^{t-1} u(c_t) + \beta\gamma n V^k,$$

subject to

$$c_t + a_{t+1} = b_t + y_t + Ra_t \text{ for } t = 1,$$

$$c_t + a_{t+1} + nb_{t-1}^k = b_t + y_t + Ra_t \text{ for } 2 \leq t \leq 4,$$

$$a_{t+1} \geqslant 0 \text{ for } 1 \leq t < 4, \tag{2}$$

$$b_{t-1}^k \geqslant 0 \text{ for } 2 \leq t \leq 4, \tag{3}$$

where V is the lifetime utility of the parent, V^k is the lifetime utility of each child, β is the discount factor, c_t is consumption, n is the exogenous number of children, $\gamma < 1$ represents the altruistic weight per child, b_t is the transfer received by the parent from his own parents, b^k_{t-1} is the transfer the parent gives to each child age $t-1$, a_t are the assets in period t, y_t is the income, and R is the gross interest rate.[3] For simplicity in (2) we assume a zero borrowing limit. Constraint (3) implies that parental transfers cannot be non-negative.

The Euler equations of this model are given by

$$u'(c_t) = \beta R_{t+1} u'(c_{t+1}) \geqslant \beta R u'(c_{t+1}) \text{ for } t < 4, \tag{4}$$

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

$$u'(c_t) \geqslant \gamma u'(c^k_{t-1}) \text{ for } 2 \leq t \leq 4, \tag{5}$$

where c^k_{t-1} is the consumption of the child and the inequality holds strictly when the parental transfer is zero, or $b^k_{t-1} = 0$. In the equation above $u'(c_t)$ is the marginal cost to the parent of transferring to the child, while $\gamma u'(c^k_{t-1})$ is the marginal benefit.

Assume that borrowing constraints are not binding after $t = 3$ ($R_4 = R$), which is a reasonable assumption for the later periods in adult life, and that utility is $u(c) = \log(c)$. As we show in the appendix, in the steady state, conditions (4) and (5) imply that the timing of parental transfers is determined by,[4]

$$1 \geqslant \gamma\beta \max\{R_2, R_3\} \geqslant \gamma\beta R_4 = \gamma\beta R, \tag{6}$$

where the following three cases with positive transfers may occur: *(i)* $g_1 > 0$ (early transfer) if $1 = \gamma\beta R_2$; *(ii)* $g_2 > 0$ (late transfer) if $1 = \gamma\beta R_3$; and *(iii)* $g_1, g_2 > 0$ (transfer in both periods) if $1 = \gamma\beta R_2 = \gamma\beta R_3$. These conditions imply that parental transfers occur in the periods in which the child is most constrained: this happens in period $t = 1$ in case *(i)*, and period $t = 2$ in case *(ii)*. Notice that case *(i)* does not preclude that the child might be also constrained in period $t = 2$, which would occur when $1 = \gamma\beta R_2 > \gamma\beta R_3 > \gamma\beta R_4 = \gamma\beta R$. However, the child does not receive a transfer in that period because the parental marginal cost of the transfer is larger than the marginal benefit. In other words, being constrained is a necessary condition for a transfer to occur, but it is not sufficient. We use the distinction between early, late and transfers in both periods to interpret longitudinal data in our empirical analysis.

In addition to binding credit constraints, the shape of the income profile plays a central role in determining the timing of transfers, another innovation relative to Altig and Davis (1989, 1992). As shown in the appendix, the transfer amount for case *(i),* the early transfer case, is given by[5],

$$b_1 = \frac{\gamma}{1 + n\gamma + \beta + \beta^2}\left[y_2 + \frac{y_3}{R} + \frac{y_4}{R^2}\right] - \frac{1 + \beta + \beta^2}{1 + n\gamma + \beta + \beta^2} y_1, \tag{7}$$

while transfer amount b_2 for case *(ii)*, the late transfer case, is given by,

$$b_2 = \frac{\gamma}{1 + n\gamma + \beta}\left[y_3 + \frac{y_4}{R}\right] - \frac{1 + \beta}{1 + n\gamma + \beta} y_2. \tag{8}$$

[3] Notice that this model is dynastic: iterating forward from one generation to the next, the model becomes infinite horizon. We solve for the stationary equilibrium with $V = V^k$. Due to the infinite horizon nature of this model, restriction $\beta\gamma n < 1$ is required for utility to be bounded.

[4] As in Altig and Davis (1989, 1992), since the model is dynastic, deterministic, and there is no income growth, we focus on the steady state solution.

[5] Notice that in the steady state of the model $c_t = c^k_t$, $b_t = b^k_t$ and $y_t = y^k_t$ for all t.

Comparative statics on these two equations imply that a higher y_1 decreases b_1. Because there is a one-period age difference between the parent and the child, a higher y_1 makes the typical income profile flatter since y_2/y_1 decreases, which reduces the income difference between the parent (y_2) and the child (y_1) and reduces parental transfers. Similarly, a higher y_2, which makes the initial income profile steeper, increasing y_2/y_1, decreasing b_2 and increasing b_1. Finally, regarding future resources, higher future income y_3 and y_4 increase both b_1 in case *(i)* and b_2 in case *(ii)*: if borrowing constraints bind in periods $t = 1$ or $t = 2$, future resources can also be used in equalizing marginal utilities across generations.

A numerical illustration of the effects of different realistic income profiles on the timing of transfers is shown in Figure 1.[6] Income profile (top panel) and transfer amounts (bottom panel) are displayed relative to y_1, which is the total income during the first period of adult life. The income profile corresponding to case *(iii)*, where transfers are given both early and late, is the steepest, with the peak occurring in period $t = 3$. As shown in the bottom panel of Figure 1, this increasing income profile allows parents to transfer to their adult children in both periods ($b_1 > 0$ and $b_2 > 0$). These parents not only give to their adult children in both periods, but they also give them larger amounts (bottom panel). The importance of the income profile can be again seen by noticing the case when the child never receives transfers. As seen in the top panel of Figure 1, when the income profile is almost flat between periods $t = 1$ and $t = 2$, which is typical among those with less than a college degree, parents do not transfer at all. In this case, the income of the child is similar to that of the parent and the marginal cost of transferring is higher than the marginal benefit to the parent. Finally, the income profile corresponding to the early transfer case ($b_1 > 0$) is not as steep as in the case when transfers occur in both periods, while that corresponding to the late transfer case ($b_2 > 0$) displays a ratio y_2/y_1 slightly lower than one, case in which the borrowing constraint is most binding in period $t = 2$.

In addition to the income profile, the number of children n also affect the timing of transfers, a prediction that we explore in HRS data. Notice that a link between transfers and number of children can be obtained in models with commitment, while models with strategic considerations have not been yet extended to the case of multiple children. Equations (7) and (8) imply that a larger n reduces transfer amount b_1 for the early transfer case, as well as transfer amount b_2 for the late transfer case. Both of these work through n diluting parental resources in the budget constraint.

2.2 Strategic games in dynamic models of parental altruism

Similar to the models of parental altruism where parents commit to the timing of transfers, models without commitment where the parent and a child behave strategically were also first explored in the early 1990s to analyze the implications of intergenerational links on Ricardian equivalence results (Bruce and Waldman, 1990). A number of papers analyzing a two-period game between the parent and a child were written, including among others the earlier work of Altonji *et al.*'s (1997), and the more recent work of Chu (2020), and Barczyk and Kredler (2021).[7] These papers examine a model where parent and child overlap for two periods, the child faces borrowing constraints in the first period, and the child's income is uncertain in the second period. Parent and child play a game where the parent is the Stackelberg leader, deciding the transfer before the child decides his own consumption and saving. As with the models with commitment, in this class of models constrained children may receive transfers, but it is also possible for unconstrained children to receive.

[6] Figure 1 assumes a period lenght of 20 years, $n = 2$, an annual interest rate of 3%, $\beta = 0.442$ and $\gamma = 0.7$. We used data from the Panel Study of Income Dynamics to verify that the examples of income profiles displayed in Figure 1 are observed in US data.

[7] Multi-period versions were also developed by Barczyk and Kredler (2014) and Boar (2020, 2021).

To explore the main insights from these models, in particular the cases where the child receives transfers early, late or in both periods, consider the following version, which summarizes Altonji *et al.* (1997) and Chu (2020). Parental utility is given by

$$V = u(c_1) + \gamma u(c_1^k) + \beta E_1[u(c_2) + \gamma u(c_2^k)],$$

and parental constraints are[8]

$$c_1 + a_2 + b_1^k = y_1 + Ra_1,$$
$$c_2 + b_2^k = y_2 + Ra_2,$$
$$b_1^k \geq 0, \text{ and } b_2^k \geq 0.$$

While parents face non-negative transfer constraints, they do not face borrowing constraints. The child's utility is given by

$$V^k = u(c_1^k) + \beta E_1[u(c_2^k)],$$

the child faces a borrowing constraint in the first period of the form,

$$a_2^k \geq 0,$$

and the child's income in the second period y_2^k is uncertain. The game occurs in three stages: in the first stage the parent decides savings a_2 and the first-period transfer to the child b_1^k (Stackelberg leader). In the second stage, the child decides his savings a_2^k. In the third stage, which occurs in the second period, the parent chooses the second-period transfer b_2^k. The timing of the game guarantees a unique solution.

Solving the model by backwards induction, the optimal second-period transfer b_2^k satisfies

$$u'(c_2) \geq \gamma u'(c_2^k),$$

which holds with equality if $b_2^k > 0$ and is similar to (5). Optimal function $b_2^k(a_2, a_2^k, y_2^k)$ depends on the assets of parent and child, as well as the realized child's income y_2^k. In this strategic game, the parent chooses $b_2^k(a_2, a_2^k, y_2^k)$ to induce allocations of consumption for himself and the child.

In the second stage of the game, the solution of the optimal child savings a_2^k depends on whether $b_2^k > 0$ or $b_2^k = 0$, and takes as given the first-period transfer b_1^k. Chu (2020) solves this problem numerically, obtaining a function of the form $a_2^k(b_1^k, y_2^k, a_2)$. An important point in Chu (2020), also made in Barczyk and Kredler (2021) but not recognized in Altonji *et al.*'s (1997), is that there are two local maximum in the child's objective function, one that corresponds to the case in which $b_2^k > 0$ and the other one to case with $b_2^k = 0$. Specifically, if the child anticipates a positive second-period transfer in a low-income state, then the child's optimal saving will be inefficiently low. But if the child expects no second-period transfers, then it is optimal to save more. These two local maxima result in a discontinuity of the child's saving function. For example, a small increase on the first-period resources of the child, say a small increase on b_1^k, could result in the child switching from the low-saving local maximum where the child expects $b_2^k > 0$ to the high-saving maximum where the child expects $b_2^k = 0$. The non-convexity of this problem limits the use of derivatives in characterizing the optimal solution.

In the first stage of the game, the parent takes the child's saving function $a_2^k(b_1^k, y_2^k, a_2)$ as given and chooses savings a_2 and the first-period transfer to the child b_1^k. Again in this case, the parent computes his objective function for the case $b_2^k > 0$ and for the case $b_2^k = 0$, and then picks the

[8] In contrast with the previous section, the model here is not dynastic: parents do not receive transfers from their own parents, and children do not give transfers to their own children. The parent is not the head of a dynasty solving an infinite horizon problem.

maximum. In deciding the first-period transfer the parent takes into account that the borrowing constraint of the child may bind, which prevents the child from smoothing consumption across the two periods . But there is a trade-off since the parent also considers that in response to a large first-period transfer, the child may undersave and expect to receive a larger second-period transfer (Samaritan's dilemma). Chu's (2020) characterization of these trade-offs results in the following three insights. First, rich parents can act as family dictators, achieving what they think is the first-best allocation. They do so by making a first-period transfer that still keeps the child constrained, so that there is no undersaving, and then giving a second-period transfer that dictates the consumption of the child. Rich parents give in both periods, giving less in the first period, and delaying transfers to the second period.

In contrast, for middle-wealth parents it is optimal to give a large first-period transfer and a zero second-period transfer: these parents make the second-period transfer inoperative, eliminating the child's undersaving problem. Children of middle-wealth parents save in the first period in anticipation of a zero second-period transfer. This possibility of front-loading transfers, also discussed in Bruce and Waldman (1990) and Barczyk and Kredler (2021), was not described in Altonji *et al.*'s (1997). The last insight from Chu (2020) is that poor parents find it optimal to delay transfers and only give in the second period. In the empirical section of the paper we follow children over a 20-year period and compare those who only receive early in the period, versus those who only receive late, and those who receive both early and late.

Ignoring the non-convexities of the problem, Altonji *et al.*'s (1997) derived the following transfer-income derivative,

$$\partial b_1^k / \partial y_1 - \partial b_1^k / \partial y_1^k = 1, \tag{9}$$

which they used to test the importance of altruism in explaining parental transfer behavior. Specifically, they tested whether an increase by one dollar in the (permanent) income of the parent coupled with a one-dollar decrease in the child's income resulted in a one-dollar increase in parental transfers. Using 1988 cross-sectional transfer data from the Panel Study of Income Dynamics (PSID), they found that redistributing one dollar from a recipient child to a donor parent leads to an increase in the transfer of much less than one dollar, which they interpreted as a strong rejection of parental altruism.

In contrast with Altonji *et al.*'s (1997) results, Chu (2020) corrects the transfer-income derivative to take into account the non-convexities of the problem and shows how the altruistic model is consistent with the same 1988 cross-sectional transfer data from the PSID. Under the corrected transfer-income derivative, redistributing one dollar from a recipient child to a donor parent may lead to an increase in the transfer of less than one dollar because the relationship between the transfer and parental income is non-monotonic. As discussed, rich parents tend to make smaller first-period transfers to a constrained child, delaying transfers for the second period, while middle-income parents make larger first-period transfers to a child who saves. If redistributing one dollar from the child to the parent results in a regime switch from a saver child to a credit constrained child, then the transfer-income derivative may be less than one, as verified in cross-sectional data. In the empirical section of the paper we examine the transfer-income derivative for both cross-sectional transfers and for total transfers over a 20-year period.

Despite the different assumptions, the two types of models discussed above generate similar predictions, with transfers occurring either early in the lifecycle, late, or both early and late. Binding borrowing constraints are associated with parental transfers in both models, although children with positive saving may receive transfers when strategic considerations are taken into account. As we do not directly observe whether children face binding borrowing constraints in HRS data, our empirical analysis does not allow us to distinguish between the two models.[9] However,

[9] Cox and Jappelli (1990) use cross-sectional data from the Survey of Consumer Finances, which contains a direct

we will follow adult children over time to characterize the types who receive early, late, or both early and late, paralleling the theoretical analysis.

3 Empirical analysis

In this section we analyze the central question of this paper, which concerns the patterns of total intervivos transfers in longitudinal data. We focus on two main aspects of the data: first, we examine the timing of transfers, documenting whether parents choose to transfer early, front-loading transfers, or if they choose to delay transfers, a central issue in dynamic models of transfers. Second, we aggregate transfers over time at the child level, computing total transfers over a 20-year period, and documenting the patterns of total transfers. Notice that the total intervivos transfers we compute are a lower bound for lifetime intervivos transfers, as we are limited by HRS data availability.

3.1 Data

Our main data source is the RAND biennial 1996-2014 HRS data (10 waves). We use the longitudinal file, the family data files, and the exit/post-exit interview files.[10] The HRS is a nationally representative panel survey of individuals age 50+ and spouses. Both the individual and the spouse are respondents to the survey. 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.

Since the main focus of our paper is the parental transfer question, and this HRS question was different in the 1992 and 1994 waves, we only use the 1996-2014 data. 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 (two years). If financial help was provided, then the total amount given to each child is asked.[11] As transfers are reported since the last wave, the 1996-2014 data gives information about transfers over a 20-year period.

Our unit of observation is a parent-kid pair. Since the focus of our analysis is total transfers received over the 20-year period, we require that for each parent-kid pair in the sample, transfers are reported (zero or positive) each of the 10 waves. Other sample selection criteria include: that there is a valid parent-kid link; that parents have either zero or one spouse during the period they are observed; that parents never split; that children are age 18 or older in the first wave they are observed; that the child is alive in every wave; that parents do not divorce or separate during the observed period; that there is consistency between the information provided by both parents; that children never coreside with the parents during the period they are observed; and that records from both parents (respondents) are collapsed so that there is one record per kid in the sample.[12] In constructing a single parent-kid pair when both parents are present, we assign the male parent as head, but retain all information concerning the spouse as part of our panel record for the every parent-kid pair.

Table 1 summarizes some economic and demographic features of our sample, which contains a total of 6,444 parent-kid pairs (64,440 panel observations over all 10 waves). All parents in our

measure of liquidity constraints (whether lenders have turned down a request for credit). They find evidence that private transfers flow to adults facing credit rationing. They also find that transfers do not appear to overcome the liquidity constraints for all recipients.

[10] We stop our analysis in 2014 which is the last year for which family data files from RAND are available.

[11] The issue with the transfer questions in 1992 and 1994 is that they ask about the amount given in the previous year only. In addition, the 1992 question included transfers totaling \$100 or more.

[12] Our sample selection criteria is similar to McGarry (2016).

sample are from the initial HRS cohort, born 1931 to 1941, as these are the only ones observed in all 10 waves. Parent heads of household are on average 70 years old and 61 years old when they are first observed in 1996, have 2.74 matched children in the sample and 12.7 years of schooling. The mean parental household income in our sample is $76,550 while mean family wealth is $655,925. Adult children are on average 43 years old and 34 years old when first observed in 1996, have 13.8 years of schooling, and household average income of $78,870. The latter value is imputed, as HRS child's income is reported in brackets rather than in continuous values.[13]

A salient feature of the data is that on average only 14% of children receive transfers in any given HRS wave, but that when we follow children over a 20-year period, 48% receive at least once. The average transfer amount by wave is $975, but conditional on receiving it is $6,938 (in a 2-year period). In contrast, the average total amount over 20 years is $9,613, and conditional on receiving it is $19,936. Both transfers by wave and total transfers exhibit high dispersion, making inequality a prevalent feature of parental intervivos transfers data.

3.2 Timing of transfers

This section describes the timing of intervivos transfers, first wave by wave, and then aggregating transfers over the early period (first five waves) and the late period (last five waves). Table 2 considers transfers by wave and reports the age profile of the probability of receiving, the transfer amount, and positive transfers. Both OLS estimations and parent-kid fixed effects are reported.[14] The main message of Table 2 is that while there is a significant age profile for both the probability of receiving and the amount, there is no age profile for positive amounts. In fact, the decreasing age profile of amount received is mostly driven by the decreasing age profile of the probability, as more zero transfers are observed as the child ages. These findings are robust to controlling for parent-kid fixed effects.

The top panel in Table 2 reports a linear age profile, which is similar to the one reported by McGarry (2016). The innovation in Table 2 is in the bottom panel, where we consider age brackets. The most interesting findings concern the regressions for transfer amounts. According to OLS estimates, those in the 25-35 age bracket receive on average $912 more than the 55-65 age bracket (omitted), while those ages 35-45 receive $530 more. This pattern is consistent with the notion that younger adults on average have less income than their parents and are more likely to face borrowing constraints. When parent-kid fixed effects are introduced, only the 25-35 age bracket is statistically significant, with children in this bracket receiving $368 more. However, looking only at those who receive positive amounts, age plays no role, suggesting that when we follow children over time, positive transfers are received at all ages, and on average on similar amounts. This pattern is consistent with the insight that while over time some children receive early transfers, other receive later transfers, and others both early and late. As discussed in the theory section, this could be due to borrowing constraints binding at different ages, or to strategic considerations where parents delay transfers.

To offer a complementary perspective on the relative size of early versus late transfers, we exploit the longitudinal nature of the data to construct measures of aggregate transfers for each

[13] We impute the child's income following a procedure similar to McGarry and constructing continuous measures using Current Population Survey (CPS) data. McGarry (2016) imputes the child's income in the HRS by using the median family income within the given income bracket for individuals in the CPS by year. In addition to family income bracket and year, we also take into account the following criteria in imputing income from the CPS: gender, 5-year age brackets, marital status (married or non-married), education (college and non-college), and work status (unemployed, part time or full time). We use properly weighted CPS data for anyone who is a head (males for couples, and either gender for singles) or a spouse.

[14] OLS estimates control for year effects. Results are robust to logit regressions for probabilities and Tobit regressions for amounts. For a simpler interpretation, here we report OLS estimates.

parent-kid pair over the first five waves (early transfers) and the last five (late transfers). As we show next section, computing total early and total late transfers allows us to characterize the heterogeneity among parent-kid pairs in our sample, particularly among those who receive positive transfers. Table 3 examines the relative size of total early versus total late transfers. As children in the sample are first observed at different ages, we control for cohort effects by introducing dummies for children's age brackets in 1996 (25-30, 30-35, 35-40 and 40-45). Consistent with the message of Table 2, the estimated dummies indicate that on average, early and late transfers are larger for younger cohorts. For example, children who were 25-30 in 1996 receive on average \$2,844 in each the early and late periods, relative to those who were 40-45 in 1996. But for all cohorts, total early transfers (zero or positive) are on average \$766 larger than late transfers, suggesting than on average parents tend to front-load transfers. As seen from the probability regressions, this early-transfers pattern is explained in part by the decreasing probability of receiving over time. Introducing parent-kid fixed effects we estimate that total early transfers are on average \$813 larger than late transfers.

But the most interesting result in Table 3 is that conditional on receiving, on average total transfer amounts are no different between the earlier and later periods, a novel result. This result echoes the one from Table 2 for transfers by wave. While the result that the probability of receiving and the transfer amount decrease as the adult child ages has been documented elsewhere (McGarry, 2016), the result that conditional on receiving there is no correlation between age and amount received is novel. Next section we use our measures of total early and total late transfers to characterize the patterns of conditional transfers.

3.3 Unpacking positive transfers

In this section we explore why positive transfer amounts are on average no different in the earlier and later periods. Table 4 explores potential composition effects of different transfer types across children, as well as the role of parental income. As discussed in the theory section, parents with different resources have different optimal transfer timings, with some delaying transfers, others front-loading transfers, and others giving both early and late. For this purpose we construct a measure of parental permanent income following Altonji *et al.*'s (1997).[15], [16] Table 4 reports the distribution of children who receive early transfers, late transfers, or both. As shown in the top panel, 52% of children never receive transfers, 17% receive only early, 10% receive only late, and 21% receive early and late. When looking at the distribution by parental permanent income, 71% of children with parents in the first income quartile (\$53,028) never receive. In contrast, 35% of children with parents in the fourth income quartile (\$278,133) never receive and 35% receive both early and late. Finally, Table 4 also indicates that the fraction of children who only receive late

[15]Specifically, we run the following regression

$$\log(Y_{it}) = \mathbf{X}_{it}\beta + e_{it},$$

where Y_{it} is the age of parent i at time t; $\mathbf{X}_{it}$ contains an age polynomial, marital status dummies, year dummies, and number of children; and error term e_{it} is given by

$$e_{it} = \nu_i + u_{it}.$$

As in Altonji *et al.* (1997) we assume that the serial correlation of u_{it} very weak, so that ν_i is the mean residual of the regression for each person. Permanent income is measured by ν_i normalized to a person age 50, married and with no children in 2014 (taking antilog).

[16]We interpret our measures of permanent income for parents with caution, since in the HRS parent's income is mostly observed after age 50, around the time income starts falling. In fact, the only statistically significant age coefficient is the linear one (negative). Despite this limitation, the measures of parental permanent income are overall reasonable and the distribution is comparable to that in Altonji *et al.* (1997), who uses PSID data.

transfers is not only the smallest, but it does not vary much across income quartiles.

While Table 4 summarizes the distribution of transfer types (early, late or both periods) by parental income quartile, Table 5 presents the estimation of a multinomial logit introducing other controls, notably child's income, child's cohort (age brackets in 1996), parental wealth, parental and child schooling, and number of siblings (early transfer only omitted).[17] Table 5 includes the sample of children who receive positive transfers either only early, only late or both. As seen in the table, relative risk ratios are only significant for children who receive in both periods. For example, relative to children with parents in the first income quartile, children with parents in the second quartile are 1.9 times more likely to receive in both periods when compared with the corresponding income quartiles among those who only receive early. The corresponding relative risk ratios are 2.6 for children with parents in the third quartile, and 3.0 for those in the fourth quartile. Table 5 also indicates that relative to children with parents in the first income quartile, children with parents in higher income quartiles are no more likely to receive late transfers only compared with those who receive early transfers only. In sum, Table 5 lends support to the insight from the strategic two-period model that parents with higher permanent income are more likely to give both early and late, so that they can both support the children when they more likely face borrowing constraints, but also postponing transfers to implement the efficient allocation. In this respect, children with high income parents receive more consistent support over the lifecycle than children with poorer parents.

The bottom half of Table 4 explores transfer amounts by transfer type and by parental permanent income. Overall, and regardless of type, average transfers are increasing in parental permanent income. Notably, regardless of parental income, those receiving both early and late receive more in the early period than those who only receive early, and receive more in the late period than those who only receive late. For example, even among children whose parents are in the first income quartile, those who only receive early get on average \$5,650, while those who receive both early and late get on average \$13,357 just on the early period (and \$23,351 total). This suggests that even controlling for parental income, parents who give both in the early and late periods also give more generously.

Table 6 tests for the statistical significance of these differences using both OLS and family fixed effect specifications among those who receive positive transfers. We run separate regressions for total early transfers and total late transfers, control for a number of observables, and we introduce a dummy for receiving transfers in both periods. As seen in the Table, this dummy is significant in all specifications. Turning the OLS estimates in the first two columns, children who receive in both periods get \$7,488 more in the early period relative to those who only receive in the early period. In addition, those who receive in both periods get \$5,407 more in the late period relative to those who only receive in the late period. This suggests that even controlling for relevant observables, there is still a difference in transfer amount between those who receive in both periods and those who receive only early or only late. To explore whether unobserved differences across parents, like degree of altruism, explain part of this difference, the last two columns of Table 6 explore the family fixed effect regressions for total early and total late transfers. Looking within families and controlling for children's income and age, the dummy for receiving in both periods is only significant for total early transfers: on average, siblings who receive in both periods receive \$5,420 more in the early period relative to those who only receive in the early period. This suggests that children in some families receive more consistent support (early and late) from parents over the 20-year period we observe them, and that this same children receive much more than siblings who only receive early.

[17] In the HRS child's income is reported less frequently than parental income. Due to limited number of observations we compute the child's average income for the sample period, rather computing permanent income using the methodology of Altonji *et al.* (1997). In addition, we are not able to control for child's wealth, as this is not reported in HRS data.

This is a novel insight and it suggests that even controlling for child's cohort and income, parents follow different strategies when timing the transfers across their children.

3.4 Total intervivos transfers

In this section we focus on the patterns of total transfers over the 20-year period. Table 7 reports the probability, mean total transfer and average positive total transfer by quartile of parental permanent income (columns). As seen in the top panel, higher parental permanent income increases the probability, total amount and total positive amount. For example, while 29% of children with parents in the first income quartile receive positive total transfers, 64% do when parents are in the fourth quartile. But interestingly, the average positive total transfer is $10,940 in the first quartile, where parent's permanent income is $53,028, and it is about three times bigger, $29,523 for the fourth quartile, even if permanent income is about five times higher ($278,133). In other words, among children who receive, total transfers are proportionally higher relative to parental permanent income for the poorer parents. In fact, Table 7 also reports the average ratio of transfers to permanent income in each quartile, as well as the corresponding average ratio for positive transfers. The average ratio of transfers to permanent income is not very different across income quartiles: it is 5.5% for the lowest and 6.7% for the highest. However, the average ratio of positive transfers to permanent income is decreasing across income quartiles: it is 19.2% for the lowest and 10.4% for the highest. Perhaps richer parents give proportionally less intervivos transfers relative to income, but subsequently give more bequests. However, as we explore later, bequests are not as prevalent: even for children with parents in the fourth income quartile, the incidence of intervivos transfers is about six times higher than that of bequests.[18] In sum, children of poorer parents who receive transfers appear to receive relatively more generous amounts.

To compare the differences between using cross-sectional (per wave) versus panel transfer data, the bottom panel of Table 7 reports the same statistics as the top but for transfer per wave, rather than for total transfers. Similar statistics for a cross-section of transfers are reported by Altonji *et al.* (1997) using 1988 PSID data (see their Table 3, p. 1140). As with total transfers, the frequency and amount of transfers per wave is increasing with income quartile. It is also the case that the average ratio of transfers to permanent income is decreasing across income quartiles: it is 8.5% for the lowest and 3.1% for the highest. But perhaps what is most interesting is that once we follow children over time and compute total transfers, this average ratio increases by almost 11 percentage points for the poorest, while it does by about 7 percentage points for the richest. In other words, when observed over a 20-year period, poorer parents give transfers to their children at a share of income even larger than that of richer parents. A question of interest here is how parental transfers compare with public transfers, which are mostly directed to adult children in the lowest quartile. It turns out that even if poorer parents transfer a larger share of their permanent income relative to rich parents, parental transfers are small relative to public transfers. For instance, in 2013 a household with an income of $53,000, which is the average income of our lowest quartile, received net public transfers of $7,800 (CBO, 2016). According to Table 7, children in the lowest quartile who receive positive parental transfers get $10,940, but over a 20-year period.

Table 7 does not control for the income of the child, nor for unobservable parental characteristics such as degree of altruism. We control for this and other observable variables in Table 8, where we regress the probability and the total transfer amount on parental permanent income, parental initial wealth, child's average income and other observables including years of schooling of parent and child, number of siblings, child's gender, child's cohort, parent race and initial age. We report both OLS regressions and family fixed effects. All reported coefficients are significant and with the

[18] The analysis including both intervivos transfers and bequests is based on a smaller sample due to data limitations in the HRS.

expected signs. For example, among those who receive positive total transfers, every extra dollar of parental permanent income translates into additional \$0.03 of total transfers. On the other hand, every extra dollar of child's average income translates into a reduction in total transfers of \$0.09. The quantitative effects are large for schooling and number of siblings: every additional year of parental schooling results in additional \$1,017 in total transfers, with an extra year of the child's schooling adding \$871. Every extra sibling reduces total transfers among those who receive in \$2,602, a sizable quantitative effect.

The family fixed effect regressions in Table 8 provide insights into the distribution of total transfers among siblings. The effects here echo the early results from McGarry and Shoeni (1995), but in the case of total transfers over a 20-year period. As shown in the table, parents do give more to children with lower income, although the point estimates are small: on average, a sibling \$1 richer receives \$0.18 less total transfers. In this respect transfers are compensatory.

3.5 The transfer-income derivative

Expanding our analysis of the relationship between parental income and transfers, in this section we examine the transfer-income derivative first estimated by Altonji *et al.* (1997) and then revisited by Chu (2020). As discussed in the theory section, the corrections of this derivative in Chu (2020) imply that a redistribution of one dollar from a recipient child to a donor parent leads to an increase in the transfer of much less than one dollar. While both Altonji *et al.* (1997) and Chu (2020) use the same 1988 cross-section of PSID data to estimate the transfer-income derivative, here we extend the analysis to include total transfers received by a child over a 20-year period.

Table 9 summarizes our computations of the transfer-income derivative, where we use a Tobit regression on transfer amounts.[19] We first compute the transfer-income derivatives for the 1996 cross-section, but then aggregate transfers from the five waves and from all 10 waves (columns). This allows us to compare how the derivatives change from cross-sectional to longitudinal data, a novel exercise. Finally, as in Altonji *et al.* (1997), we compute both the uncorrected and the corrected derivatives. Specifically, while the uncorrected derivative is computed from the marginal effects among those who receive positive transfers, the corrected derivative adds the effect obtained from children who were initially not receiving transfers, but as a result of the income redistribution between the child and the parent, will now receive positive transfers.

To clarify the difference between the uncorrected and corrected derivatives, using the notation from equation (9) in the theory section of the paper, we can write the corrected derivative for a change in parental income as,[20]

$$E\left[\left.\frac{\partial b_1^k}{\partial y_1}\right|\mathbf{z},b_1^k>0\right]=\frac{\partial E\left[\left.b_1^k\right|\mathbf{z},b_1^k>0\right]}{\partial y_1}+\frac{\partial P\left[\left.b_1^k>0\right|\mathbf{z}\right]}{\partial y_1}\frac{E\left[\left.b_1^k\right|\mathbf{z},b_1^k>0\right]}{P\left[\left.b_1^k>0\right|\mathbf{z}\right]}, \tag{10}$$

where $\mathbf{z}$ refers to observable characteristics for the parent-kid pair. The first term on the right-hand side is the uncorrected derivative, or the marginal effect among those who receive, and the second term accounts for the effect the change in parental income has on the probability of giving a positive amount. A similar formula can be written for changes in the child's income, so that the corrected transfer-income derivative is given by,

$$E\left[\left.\frac{\partial b_1^k}{\partial y_1}\right|\mathbf{z},b_1^k>0\right]-E\left[\left.\frac{\partial b_1^k}{\partial y_1^k}\right|\mathbf{z},b_1^k>0\right].$$

[19] Altonji *et al.* (1997) use a structural and non-parametric approach to compute the transfer-income derivative. Here we follow Chu (2020) and use a Tobit model.

[20] See equations (6) and (8) in Altonji et al. (1997).

As in Altonji *et al.* (1997), the corrected transfer-income derivatives in Table 9 are larger than the uncorrected ones. But the most interesting result in Table 9 is that as we move across columns from considering the 1996 cross-section to aggregated transfers up to the full 20–year period, the transfer-income derivative becomes larger, going from \$0.086 (1996 cross-section) to \$0.249 (total transfers) for every redistributed dollar from child to parent. Altonji *et al.* (1997) obtained similarly small estimates for their 1988 cross-section, specifically \$0.054, which is close to what we estimate, since the PSID measures transfers over a one-year period, while they are measured over a two-year period in the HRS.[21] To understand the reason why the transfer-income derivatives in Table 9 increase as we aggregate transfers over time, notice that there are two conflicting forces: first, the probability of receiving positive transfers $P\left[b_1^k > 0 \middle| \mathbf{z}\right]$ increase as we follow children over longer periods of time because there are more chances to observe children who receive in different periods. This tends to decrease the transfer-income derivative as can be seen on the last term of equation (10): as more and more children receive positive transfers at least once, the set of potential parents who switch from giving zero to giving positive transfers is smaller. On the other hand, as transfers are aggregated over more periods, by definition the conditional expected transfer value $E\left[b_1^k \middle| \mathbf{z}, b_1^k > 0\right]$ increases, which tends to increase the transfer-income derivative (last term of equation 10). On net we estimate that the latter effect dominates, a novel insight. Our estimation of the transfer-income derivative is closer to the theoretically relevant measure for the two-period model strategic game discussed above, as we observe children over a 20-year period and compute total transfers. In this respect, panel data provides a unique opportunity to revisit the transfer-income derivative implied by models of parental altruism.

3.6 Siblings and total transfers

While the assumption that altruistic parents can commit to a schedule of transfers is strong, an advantage of the model with commitment is that it makes it possible to analyze the role of family size, while models with dynamic strategic interaction have not been yet extended to include multiple children. Table 10 considers the subsample of parent-kid pairs with transfer information for multiple children from the same family. It reports age, probability, total transfer amount and positive transfers for two, three and four siblings in the sample. The table suggests multiple children do dilute the transfers, as predicted from equations (7) and (8) above, which applies to all the probability, total amount and positive amounts. Table 10 also suggests that younger siblings on average receive more than older children, regardless of whether they are from families with two, three or four children.

Table 11 looks further into total transfers received by siblings in families of different sizes. It evaluates whether parental intervivos transfers are equalized among siblings in the same family. Family fixed-effect regressions for total transfer amount and positive amounts are estimated separately by family size. The overall message of the table is that total transfers are not equalized among siblings. Once we control for the child's average income, child's years of schooling and the child's cohort (age bracket in 1996), we find that transfers are compensatory among siblings, with poorer children within families receiving more support. This echoes the findings from the family fixed effect estimates of Table 8, but the novelty from Table 11 is that the extent of the compensation varies by family size. For every \$10,000 difference in average child income, the poorer child receives \$2,738 more total transfers in a two-kid family, while the compensation is \$1,603 in a four-kid family (positive amounts).

[21] See Table 7 in Altonji *et al.* (1997), which reports the transfer-income derivative when a dollar of permanent income is redistributed from the child to the parent.

4 Extensions

In this section we provide additional insights by extending our empirical analysis in two ways. First, we examine the sample of parent-kid pairs for which a parental death occurs to document the joint distribution of total intervivos transfers and bequests. Second, we consider the case of adult children who coreside with their parents at some point during 1996-2014 and compare their total intervivos transfers with those of non-coresident children.

4.1 Intervivos transfers and bequests

Although the incidence of bequests is lower than that of intervivos transfers, they constitute another major form of intergenerational giving (Gale and Scholz, 1994). To analyze the joint distribution of total transfers and bequests we now focus on a smaller sample for which a parental death occurs during the observed period, which includes 767 parent-kid pairs.[22] Since the majority of our baseline sample consists of parents in stable couples, most of the bequests we observe are the side bequests received when the first parent dies. As we document, side bequests are smaller than the bequests received when the surviving parent dies, but both have similar distributions, concentrated among high-income families. In contrast, intervivos transfers occur across the whole income distribution.

Table 12 summarizes our main findings on total intervivos transfers and bequests by considering two samples. The top panel includes side bequests only, which occur for the majority of our sample (615 parent-kid pairs). The bottom panel includes all the bequest information we have, both side bequests and also those given to children who had one surviving parent in 1996, with this parent dying during the sample period (1996-2014). Both the top and the bottom panels of Table 12 show statistics for the whole sample and for the highest parental income quartile. In our sample bequests are basically zero for all children with parents in the bottom three quartiles, so all the bequest information is in the top quartile.

Regarding side bequests (top panel), we find that they are overall small, even for parents in the top quartile. On average side bequests are only \$594, which is even smaller than the average transfer per wave (\$975 in Table 1). In fact, average total intervivos transfers are \$3,621, six times bigger than side bequests. Even among parents in the fourth quartile, average total intervivos transfers are larger than side bequests: they are \$7,148 and \$2,397 respectively. It is only for parents in the 99th percentile of the top quartile that side bequests are higher than total intervivos transfers: they are \$109,225 and \$74,231 respectively. The fact that side bequests are relatively small, except for the very rich, is confirmed in columns (3), (4) and (5) of Table 12. Column (3) reports average bequests as a percent of average total parental gifts (average total intervivos transfers plus side bequests): even for the top quartile, this share is 25%. Column (4) reports the average side bequests relative to average total intervivos transfers: while the overall ratio is 0.16, for children with parents in the highest income quartile it is 0.33. Last, column (5) is like column (4), but rather than computing the ratios of averages, it computes the averages of the individual-level ratios. Column (5) underscores the concentration of bequests: at the 99th percentile of the sample, the average ratio of bequests to total intervivos transfers is 8.5, while at the mean it is 0.56. But when looking within the highest parental income quartile, this ratio is 68.5 at the 99th percentile, and 1.6 at the quartile mean.

The bottom panel of Table 12 reports the same statistics as the top, but for a sample that includes both side bequests and bequests given when a widow parent dies. Bequests are highly concentrated in the top quartile of parental income, as it was the case for side bequests. For the overall sample, the probability of receiving a bequest is 2% and the average bequest amount is only

[22] We interpret the results of this section with caution given the small sample size. Our results are nonetheless informative.

$2,298. Similar patterns for the incidence of bequest are reported in Gale and Scholz (1994). Notice how incidence is higher in the top quartile, at a rate of 7% and with an average bequest amount of $9,437. But the most interesting result here is that for the average child, even for the average child with a parent in the top quartile, total intervivos transfers are comparable with bequests. This result is novel relative to the widely cited paper by Gale and Scholz (1994): while they only have a cross-section of data from the SCF, here we are able to compute total intervivos transfers from panel data and compare them with bequests. It is only at very high income levels that bequests are larger than total intervivos transfers: at the 99th percentile of the top quartile, bequests are $296,067 while total intervivos transfers are $78,824.

As seen in column (3) in the bottom panel of Table 12, average (zero and positive) bequests account for about 40% of average parental gifts, which implies that average intervivos transfers over a 20-year period account for the remaining 60%. For the top income quartile these magnitudes are reversed, with bequests accounting for 57% of total gifts and total transfers for the remaining 43%. These statistics suggest that for most families, intervivos transfers are the most important financial gift adult children receive. Notice that these statistics must be interpreted with caution as we measure only a lower bound for total intervivos transfers, and as the majority of the bequests we observe are side bequests, which tend to be smaller. However, since bequest are highly concentrated in the top income quartile, for the average individual the relative importance of total intervivos transfers we measure can be interpreted as a lower bound.

Next, as seen in column (4) of the bottom panel, while the average bequests relative to average total intervivos transfers is 0.65, for children with parents in the highest income quartile it is 1.31. Last, column (5) highlights once more the concentration of bequests: at the 99th percentile of the sample, the average ratio of bequests to total intervivos transfers is 4.9, while at the mean it is 0.5. But when looking within the highest parental income quartile, this ratio is 68.5 at the 99th percentile, and 1.4 at the quartile mean. In sum, except for the very rich, for whom the average ratio of bequests to intervivos transfers is 4.9, for the typical individual total intervivos transfers are about twice the size of bequests.

4.2 Coresidency

So far we have only considered a sample of non-coresident adult children. But coresidency with parents could be considered another form of transfer. Since imputing an amount to this type of transfer is difficult, here we focus on comparing total intervivos transfers received by adult children who never coreside, with the transfers received by children who coreside with parents at some point during the sample period. For this purpose, we add to our baseline sample adult children for whom we observe transfers in all waves, but who might have coresided with the parent at least once during 1996-2014. There are 1,595 parent-kid pairs who reported coresiding in at least one of the HRS waves, with about 532 of them reporting it once, 315 twice, 202 three times, 132 four times, and the rest more than four times. The top panel of Table 13 compares some statistics of our baseline sample of adult children who never coreside (6,444 parent-kid pairs) with the sample of those who report coresiding at least once (1,595 parent-kid pairs). As seen in the table, both the parent and the child who coreside have lower income and wealth relate to non-coresidents. But more interestingly, 67% of coresident adult children receive transfers over the 20-year period, relative to 48% of non-coresidents. Coresidents also receive more, with the average total transfer of $16,751 relative to $9,613 for non-coresidents. Conditional on receiving, the average total transfer is $24,793 for coresidents, versus $19,936 for non-coresidents. Last, coresidents also receive higher bequests, which on average are $3,562 versus $2,298.[23] In sum, if an adult child ever coresides with the parent, we observe on average larger total transfers to that child.

[23] As in the case of Table 12, most of the observed bequests in our sample are side bequests.

Notice that if the family arrangement is that the adult child does not pay rent to the parent, then the transfers reported in Table 13 for coresidents may be interpreted as a lower bound. However, it might be that the coresident child receives larger transfers as a form of payment from an elder parent who needs home care, an exchange motive. The bottom panel of Table 13 examines the age distribution of adult children and parents who coreside. Since for the majority of adult children in our sample coresidency is a short-term occurrence, we compute the age distributions only for the periods in which coresidency occurs versus those in which it does not. As seen in the table, coresidency occurs in all brackets of the child and parent age distributions. However, in our sample children who coreside tend to be younger: 30% of adult children are ages 25-35 when they coreside with parents, while among those who do not coreside, 17% are in this age bracket. Parents also tend to be younger: 35% of parents are ages 55-65 when they coreside with adult children, while among those who do not coreside, 22% are in this age bracket. These statistics suggest that if anything, coresidence tends to be a way in which younger parents support young adult children while they get established as independent adults. In sum, Table 13 suggests that relative to adult non-coresident children, children who coreside tend to be younger and receive more total transfers from their parents.

Table 14 is like Table 8, but for the combined sample of those who never coreside and those who coreside at some point. Table 14 confirms that even controlling for other observables, being a coresident sometime in our sample period is associated with $4,362 additional average total transfers than those who never coreside. Conditional on receiving this difference is $4,236. The rest of the coefficients in Table 14 are similar in magnitude and significance to those in Table 8.

5 Concluding comments

This paper exploits longitudinal data to follow adult children over time and document the extent of the financial support they receive from their parents. We find that over a 20-year period, about half of adult children across all quartiles of the parental income distribution receive intervivos transfers. This support varies widely with income, with 29% of children with parents in the lowest income quartile receiving on average $10,940, and 64% of children with parents in the highest quartile receiving on average $29,523. Interestingly, parents in the lowest quartile of our sample (average permanent income of around $53,000) give relatively more generously than those in the top quartile (average income of around $278,000).

Longitudinal data is also useful to uncover the transferring strategies parents follow. Conditional on receiving, we document how the age of the child is uncorrelated with the transfer amount. When we aggregate transfers over time and split them into early (first 10 years of HRS data) and late transfers (last 10 years), we find a variety of transfer patterns in the data, with some children receiving only early, others only late, and other both early and late. Although these different transfer types occur at all levels of parental income, we find that relative to parents giving transfers only early, parents in the top quartile are three times more likely to give in both periods relative to those in the bottom quartile. In terms of timing of transfers, children with high income parents receive more consistent support over the lifecycle than children with poorer parents.

Our analysis also gives us insights into transfers within families. Even when following children over time and aggregating transfers, total transfers are not equalized across siblings. Transfers are compensatory, supporting children with lower income, but the extent of the compensation varies with family size. On average, each additional sibling reduces total transfers by around $2,600. We also find evidence that parents follow different transferring strategies among their children, giving more generously and more consistently over time to some of them and not to others, even when controlling for income.

The facts we document in this paper provide insights into the extent of intervivos transfers in the United States. A question remains on whether these patterns hold in countries with different institutional settings, including public transfers and estate taxation. We leave this question for future research.

References

[1] Altig, D. and Davis, S. (1989). "The Timing of Intergenerational Transfers, Tax Policy, and Aggregate Savings," Working Paper.

[2] Altig, D. and Davis, S. (1992). "The Timing of Intergenerational Transfers, Tax Policy, and Aggregate Savings," *American Economic Review*, 82, 1199-1220.

[3] Altonji, J., Hayashi, F. and Kotlikoff, L. (1997). "Parental Altruism and Inter Vivos Transfers: Theory and Evidence," *Journal of Political Economy*, 105, 1121-1166.

[4] Barczyk, D. and Kredler, M. (2021). "Blast from the Past: The Altruism Model is Richer than You Think," *Journal of Economic Theory*, 198.

[5] Barczyk, D. and Kredler, M. (2014). "Altruistically Motivated Transfers under Uncertainty," *Quantitative Economics*, 5, 705-749.

[6] Boar, C. (2020). "Dynastic Precautionary Savings," *NBER Working Paper* 26635.

[7] Boar, C. (2021). "Dynastic Precautionary Savings," *Review of Economic Studies*, forthcoming.

[8] Bruce, N. and Waldman, M. (1990). "The Rotten-Kid Theorem Meets the Samaritan's Dilemma," *Quarterly Journal of Economics*, 105, 155-165.

[9] Chu, Y. (2020). "Testing Parental Altruism: A Full Solution to a Dynamic Model of Altruistic Transfers," Manuscript.

[10] Congretional Budget Office, (2016). "The Distribution of Household Income and Federal Taxes, 2013," www.cbo.gov/publication/51361.

[11] Cordoba, J. C. and Ripoll, M. (2019). "The Elasticity of Intergenerational Substitution, Parental Altruism and Fertility Choice," *Review of Economic Studies*, 86, 1935-1972.

[12] Cox, D. and Jappelli, T. (1990). "Credit Rationing and Private Transfers: Evidence from Survey Data," *Review of Economics and Statistics*, 72, 445-454.

[13] Cox, D. and Rank, M. (1992). "Inter-Vivos Transfers and Intergenerational Exchange," *Review of Economics and Statistics*, 74, 305-314.

[14] Gale, W. and Scholz, J. (1994). "Intergenerational Transfers and the Accumulation of Wealth," *Journal of Economic Perspectives*, 8, 145-160.

[15] Hurd, M., Smith, J. and Zissimopoulos, J. (2011). "Intervivos Giving over the Lifecycle," *RAND Working Paper* 524-1.

[16] McGarry, K. and Shoeni, R. (1995). "Transfer Behavior within the Family: Results from the Asset and Health Dynamics Survey," *NBER Working Paper* No. 5099.

[17] McGarry, K. (2016). "Dynamic Aspects of Family Transfers," *Journal of Public Economics*, 137, 1-13.

[18] Scholz, J., Seshadri, A. and Sicinski, K. (2014). "Long-Run Determinants of Intergenerational Transfers," Michigan Retirement Research Center, Working Paper 2014-312.

Figure 1. Illustration of life-cycle profiles for different transfer types

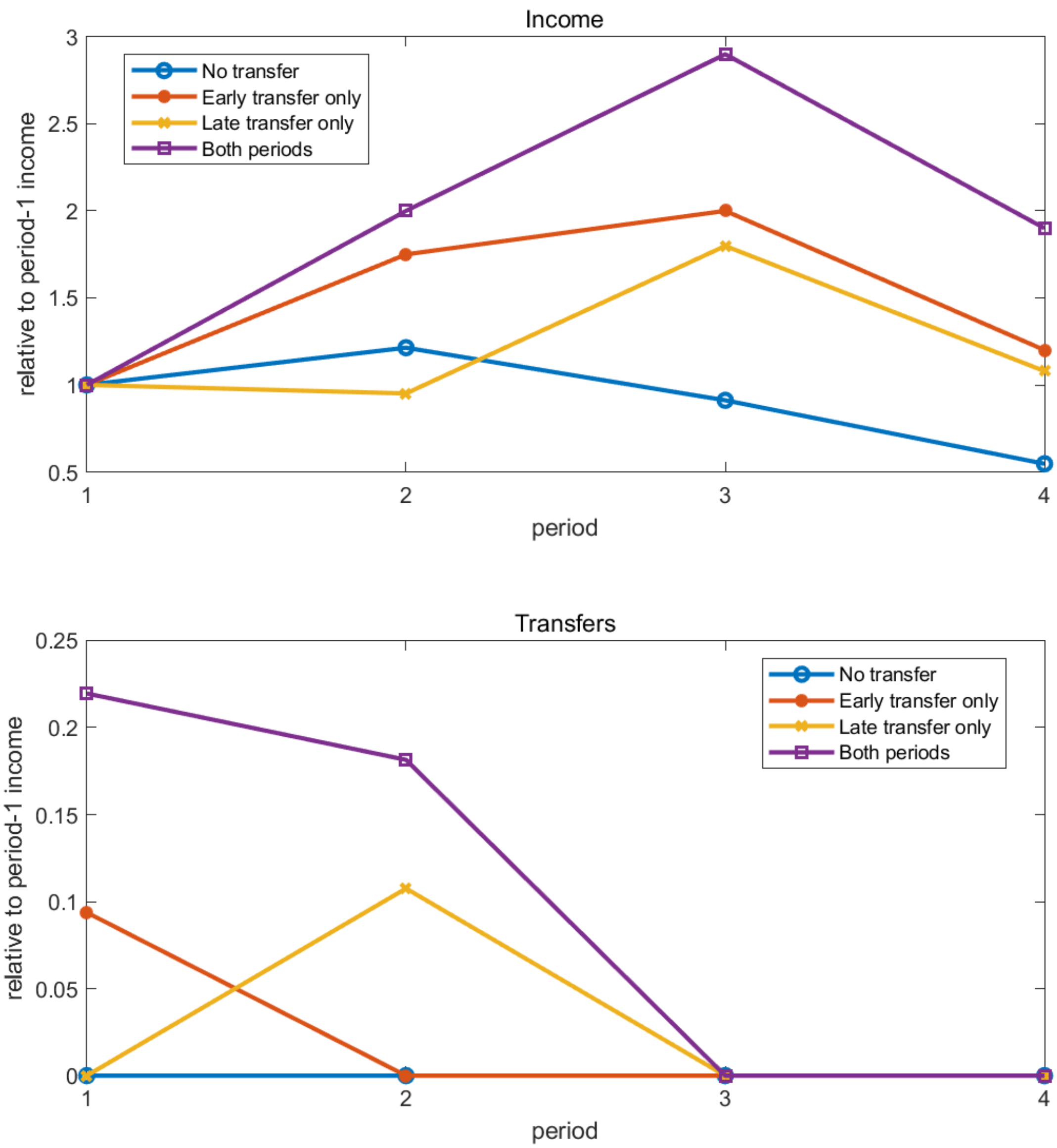

TABLE 1
Summary statistics

	Mean	Standard deviation
Variables for parent:		
Age	70.31	7.60
Age in 1996	61.13	5.07
Number of matched children	2.74	1.57
Years of schooling	12.68	3.11
Family income	$76,550	$99,956
Family wealth	$655,925	$1,485,722
Variables for child:		
Age	42.95	8.03
Age in 1996	33.74	5.70
Years of schooling	13.84	2.21
Family income (imputed)	$78,870	$44,390
Transfer per-wave:		
Received a transfer	14%	
Amount	$975	$4,490
Amount > 0	$6,938	$10,098
Total transfers:		
Received a transfer	48%	
Amount	$9,613	$24,878
Amount > 0	$19,936	$32,831
Sample size:		
Unique parent-kid pairs	6,444	
Total panel observations	64,440	

Notes: All statistics are weighted using HRS sample weights. HRS data on child's family income is reported in brackets. A continuous child's family income is imputed using CPS data for those with the same income bracket, gender, age bracket, marital status, education, work status and year. Transfer per wave corresponds to transfers over a 2-year period. Total transfers are aggregated over a 20-year period (1996-2014). Dollar amounts are expressed in 2014 U$.

TABLE 2

Age profile of intervivos transfers per wave

	OLS models			*Parent-kid pair fixed effects*		
Dependent variable →	Probability	Transfer amount	Positive amount	Probability	Transfer amount	Positive amount
Linear age fit						
Age	-0.00564***	-42.16***	-24.52	-0.00348***	-19.43***	6.468
	(0.001)	(7.22)	(34.68)	(0.000)	(4.6)	(39.5)
Constant	0.386***	2736.7***	7488.1***	0.290***	1810.5***	6674.0***
	(0.023)	(290.7)	(1246.3)	(0.016)	(201.4)	(1619.7)
R^2	0.01	0.01	0.01	0.29	0.24	0.20
Ten-year age brackets						
25-35 dummy	0.128***	912.7***	459.8	0.0807***	368.5***	-1271.8
	(0.015)	(180.0)	(1035.9)	(0.010)	(123.8)	(1232.0)
35-45 dummy	0.0639***	530.5***	732.4	0.0318***	134.9	-953.1
	(0.011)	(131.8)	(914.5)	(0.008)	(94.8)	(1155.4)
45-55 dummy	0.0362***	295.0***	443.6	0.0194***	66.62	-985.4
	(0.007)	(98.8)	(792.1)	(0.007)	(78.9)	(1052.1)
Constant	0.0851***	632.5***	7241.6***	0.107***	828.6***	7910.4***
	(0.007)	(97.3)	(797.5)	(0.007)	(79.3)	(1037.3)
R^2	0.01	0.01	0.01	0.29	0.25	0.21
N	63,470	63,470	8,355	63,470	63,470	8,355

Notes: Omitted age bracket is 55-65 years old. Transfer amount includes zero and positive amounts. Year dummies are included for OLS models. Standard errors are clustered at parent-kid level. Start superscripts: * $p < 0.10$, ** $p < .05$, *** $p < 0.01$.

TABLE 3

Timing of intervivos transfers – Aggregated early versus late transfers

	OLS models			*Parent-kid pair fixed effects*		
Dependent variable →	Probability	Transfer amount	Positive amount	Probability	Transfer amount	Positive amount
Early transfers dummy	0.0575***	765.8***	-145.3	0.0580***	812.7**	1919.4
(first five waves)	(0.009)	(253.1)	(720.1)	(0.013)	(342.2)	(1773.7)
Kid ages 25-30 in 1996 dummy	0.127***	2844.3***	3496.4**			
	(0.021)	(655.8)	(1586.6)			
Kid ages 30-35 in 1996 dummy	0.0764***	1939.1***	3048.6**			
	(0.018)	(500.8)	(1350.2)			
Kid ages 35-40 in 1996 dummy	0.0448***	1270.3***	2383.7*			
	(0.017)	(482.5)	(1398.2			
Constant	0.247***	2754.4***	11426.3***	0.313***	4372.9***	12958.7***
	(0.017)	(384.1)	(1136.4)	(0.006)	(165.4)	(932.7)
N	11,857	11,857	3,889	11,857	11,857	3,889
R^2	0.01	0.01	0.01	0.41	0.54	0.33

Notes: Each parent-kid pair has two observations: one for the early transfers (first five waves) and one for the late transfers (second five waves). Transfer amount refers to the total received in the early and the late periods (over 10 years each). Dummy for late transfers and kid ages 40-45 in 1996 are omitted. Standard errors clustered at parent-kid level. Start superscripts: * $p < 0.10$, ** $p < .05$, *** $p < 0.01$.

TABLE 4

Distribution of transfer types by timing of transfers and parental permanent income

	No transfers	*Early transfer only*	*Late transfer only*	*Both periods*		
				Total	*Early transfers*	*Late transfers*
Distribution of transfer types (%)	52%	17%	10%	21%		
Distribution of transfer types by parental permanent income (%)						
First quartile ($53,028)	71%	13%	8%	8%		
Second quartile ($93,405)	54%	18%	10%	18%		
Third quartile ($135,908)	49%	16%	12%	23%		
Fourth quartile ($278,133)	35%	19%	11%	35%		
Total transfer received ($)	0	8,052	7,922	35,294	18,632	16,661
Total transfer received ($) by parental permanent income						
First quartile ($53,028)	0	5,650	7,950	23,351	13,357	9,994
Second quartile ($93,405)	0	7,451	6,153	25,950	13,804	12,145
Third quartile ($135,908)	0	8,620	6,347	30,148	15,837	14,311
Fourth quartile ($278,133)	0	9,596	11,485	45,698	23,799	21,899

Notes: "Early transfers only" refers to receiving only in the first five waves (10 years). "Late transfers only" refers to receiving only in the second five waves (10 years). Total transfers are aggregated over the 10-year period (five waves). Average permanent income is shown in parenthesis for every income quartile. Dollar amounts are expressed in 2014 U$.

TABLE 5

Multinomial logit for transfer types

Base outcome – Early transfers only

	Relative risk ratio	*Robust standard error*
Late transfer only		
Second quartile ($93,405)	1.010	0.230
Third quartile ($135,908)	1.309	0.305
Fourth quartile ($278,133)	1.052	0.274
Constant	0.376	0.470
Both periods transfer		
Second quartile ($93,405)	1.860***	0.385
Third quartile ($135,908)	2.552***	0.548
Fourth quartile ($278,133)	3.000***	0.704
Constant	0.248	0.252
Likelihood ratio chi-square = 138.21		
Prob > chi-square = 0.000		
N = 2,323		

Notes: "Early transfers only" refers to the category of those receiving only in the first five waves (10 years). "Late transfers only" refers to the category of those receiving only in the second five waves (10 years). Additional control variables include parental years of schooling, race, initial age, and wealth; child's average income, schooling, number of siblings, gender, and child's cohort dummies (by age brackets in 1996). Average permanent income is shown in parenthesis for every income quartile. First quartile of parental permanent income ($53,028) is omitted. Standard errors clustered at the family level. Start superscripts: * $p < 0.10$, ** $p < .05$, *** $p < 0.01$.

TABLE 6

Early and late conditional total transfer amounts received by children

	OLS models		Family fixed effects	
Dependent variable →	Early total transfer amounts	Late total transfer amount	Early total transfer amounts	Late total transfer amounts
Parental permanent income ($10,000s)	75.9 (89.4)	184.7* (106.2)		
Both periods dummy	7488.4*** (969.7)	5406.6*** (1032.6)	5420.3** (2676.9)	1027.8 (2859.8)
Parental initial wealth ($10,000s)	62.5*** (9.9)	27.87** (12.3)		
Child average income ($10,000s)	-285.4 (190.0)	-287.6 (218.9)	-985.6** (442.8)	-585.1 (421.5)
N	1,804	1,536	1,817	1,548
R^2	0.24	0.13	0.43	0.59

Notes: Regressions exclude those who never receive. Early and late total transfer amounts include both zero and positive. Both periods dummy is one if child receives positive transfers both in the early and late periods. Additional control variables include parental year of schooling, race, and initial age; child's schooling, number of siblings, gender, and cohort dummies (age brackets in 1996). Standard errors clustered at the family level. Start superscripts: * $p < 0.10$, ** $p < .05$, *** $p < 0.01$.

TABLE 7

Total transfers and transfers per wave by parental permanent income quartiles

	Permanent income quartile of the parent				
	Lowest ($53,028)	Second ($93,405)	Third ($135,908)	Highest ($278,133)	Total ($142,717)
Total transfers (20 years)					
Probability	0.29	0.46	0.51	0.64	0.48
Mean amount	3,141	6,648	8,820	18,863	9,557
Conditional amount	10,940	14,420	17,358	29,523	19,974
Mean share of parental income	5.5%	7.0%	6.4%	6.7%	6.4%
Conditional share of parental income	19.2%	15.1%	12.5%	10.4%	13.4%
Transfers per wave					
Probability	0.06	0.12	0.14	0.21	0.14
Mean amount	319	659	885	1,924	970
Conditional amount	4,848	5,416	6,204	9,077	7,035
Mean share of parental income	0.5%	0.6%	0.6%	0.6%	0.6%
Conditional share of parental income	8.5%	5.7%	4.4%	3.1%	4.6%

Notes: Transfers per wave in HRS data are 2-year transfers. Total transfers are computed as aggregated transfers over all 10 waves (20-year period). Dollar amounts are expressed in 2014 U$.

TABLE 8

Probability and total amount received by children

Dependent variable →	*OLS models* Probability	Transfer amount	Positive amount	*Family fixed effects* Probability	Transfer amount	Positive amount
Parental permanent income	0.00464***	316.4***	306.4**			
($10,000s)	(0.001)	(120.9)	(149.1)			
Parental initial wealth	0.000617***	91.29***	91.89***			
($10,000s)	(0.000)	(17.8)	(19.5)			
Parental years of schooling	0.0272***	558.6***	1016.9***			
	(0.004)	(187.9)	(359.1)			
Child average income	-0.0246***	-930.0***	-860.8***	-0.0388***	-1226.2***	-1873.2***
($10,000s)	(0.003)	(158.0)	(274.8)	(0.004)	(186.1)	(505.6)
Child years of schooling	0.0165***	683.5***	871.2**	0.00808	247.4	871.8
	(0.005)	(227.9)	(395.9)	(0.007)	(250.9)	(694.3)
Number of siblings	-0.0445***	-1554.2***	-2601.8***			
	(0.006)	(249.2)	(479.5)			
N	4,662	4,662	2,323	4,662	4,662	2,323
R^2	0.14	0.22	0.21	0.49	0.63	0.52

Notes: Total amount is computed aggregating transfers at the parent-kid level over 20 years of data (1996-2014). Additional control variables include parental race, and initial age; child's gender, and cohort dummies (age brackets in 1996). Standard errors clustered at the family level. Start superscripts: * $p < 0.10$, ** $p < .05$, *** $p < 0.01$.

TABLE 9

Transfer-income derivatives

Dependent variable →	Transfers first wave	Total transfers first five waves	Total transfers all ten waves
Average marginal effects on conditional amount			
Parental permanent income	30.5^{***}	76.5^{***}	179.8^{***}
($10,000s)	(9.673)	(25.5)	(47.6)
Child average income	-176.6^{***}	-472.8^{***}	-706.2^{***}
($10,000s)	(20.2)	(56.9)	(90.1)
N	5,048	5,048	5,048
R^2 / *Pseudo* R^2	0.03	0.02	0.02
Average marginal effects on probability of giving			
Parental permanent income	0.0025^{***}	0.0034^{***}	0.0052^{***}
($10,000s)	(0.001)	(0.001)	(0.001)
Child average income	-0.0149^{***}	-0.0212^{***}	-0.0204^{***}
($10,000s)	(0.001)	(0.002)	(0.002)
Model-implied statistics			
Probability of giving positive transfer	0.198	0.353	0.430
Expected positive transfer amount	$7,383	$16,961	$26,922
Transfer-income derivative (difference)			
Uncorrected derivative	0.021	0.055	0.089
Corrected derivative	0.086	0.173	0.249

Notes: All regressions are Tobit models. Transfers in the first wave correspond to the 1996 cross-section of HRS data. Total transfers on the first five waves are aggregated transfers at the parent-kid level for the 1996, 1998, 2000, 2002 and 2004 cross-sections of the HRS. Total transfers aggregate over all 10 waves of the HRS (1996-2014). Transfer-income derivative refers to the difference between the derivative with respect to parental and child's income. Additional control variables include child's schooling, gender, and number of siblings; parent's schooling, race, and initial wealth; and cubic terms in the ages of the parent and child. Standard errors clustered at the family level. Start superscripts: * $p < 0.10$, ** $p < .05$, *** $p < 0.01$.

TABLE 10

Total intervivos transfers to different children by family size and birth order

	Birth order			
	First kid	Second kid	Third kid	Fourth kid
Families with two kids				
N=715				
Mean age	35	31		
Probability	0.59	0.60		
Mean amount	\$13,103	\$15,632		
Conditional amount	\$22,150	\$25,851		
Families with three kids				
N=487				
Mean age	37	34	30	
Probability	0.48	0.49	0.58	
Mean amount	\$8,661	\$9,459	\$13,807	
Conditional amount	\$18,196	\$19,402	\$23,720	
Families with four kids				
N=280				
Mean age	39	36	33	29
Probability	0.45	0.40	0.43	0.49
Mean amount	\$4,897	\$6,002	\$6,063	\$8,432
Conditional amount	\$10,855	\$15,041	\$14,162	\$17,152

Notes: Total transfers are computed aggregating transfers at the parent-kid level over 20 years of data (1996-2014). Dollar amounts are expressed in 2014 U\$.

TABLE 11

Family fixed effect regressions for total amount received by family size and birth order

	Two-kid family		*Three-kid family*		*Four-kid family*	
	Transfer amount	Positive amount	Transfer amount	Positive amount	Transfer amount	Positive amount
Child average income	-2005.4^{***}	-2738.0^{*}	-1511.7^{***}	-1870.8^{**}	-982.2^{***}	-1603.6^{***}
($10,000s)	(679.5)	(1507.1)	(359.3)	(905.9)	(307.8)	(561.7)
Child years of schooling	478.6	1679.5	381.9	1332.2	198.3	377.8
	(1022.1)	(2508.1)	(526.2)	(1263.4)	(441.2)	(1206.5)
Constant	20945.0	12947.7	10344.2	-581.3	10250.9	19277.9
	(13516.8)	(32103.8)	(8225.0)	(20612.9)	(6216.4)	(17159.8)
N	1,099	675	1,148	620	774	347
R^2	0.54	0.40	0.60	0.57	0.35	0.30

Notes: Additional control variables include child's gender, and cohort dummies (age brackets in 1996). Standard errors clustered at the family level. Start superscripts: * $p < 0.10$, ** $p < .05$, *** $p < 0.01$.

TABLE 12

Total intervivos transfers and bequests

	Total intervivos transfers (1)	Bequests (2)	Average bequest as % of total gifts (3)	Ratio of mean bequests to mean transfers (4)	Average kid-level bequest to transfer ratio (5)
Side bequests only (*N = 615*)					
Total ($91,776):					
Probability	0.30	0.02			
Mean amount	$3,621	$594	14.1%	0.16	0.56
99th percentile	$58,131	$493			8.5
Highest parental income quartile ($168,063):					
Probability	0.46	0.06			
Mean amount	$7,148	$2,397	25.1%	0.33	1.6
99th percentile	$74,231	$109,225			68.5
All bequests (side and final bequests *N = 767*)					
Total ($91,015):					
Probability	0.30	0.02			
Mean amount	$3,520	$2,298	39.5%	0.65	0.50
99th percentile	$58,131	$10,922			4.9
Highest parental income quartile ($161,427):					
Probability	0.45	0.07			
Mean amount	$7,229	$9,437	56.6%	1.31	1.4
99th percentile	$78,824	$296,067			68.5

Notes: The side bequests sample (top panel) contains children from stable couples who receive a bequest when the first parent dies. The sample with all bequests (bottom panel) includes both side bequests, and children with one surviving parent in 1996 who dies and leaves a bequest during the sample period (1996-2014). “Total gifts” refers to total intervivos transfers plus bequests. Average permanent income is shown in parenthesis for the total and for the top income quartile. Dollar amounts are expressed in 2014 U$.

TABLE 13

Coresident versus non-coresident adult children

13.1 – Summary statistics for income, wealth, transfers, and bequests

Panel A - Variables	*Never coresident with parent*	*Coresident with parent at least one wave*
Income and wealth		
Parent permanent income	\$136,153	\$118,299
Parent wealth in 1996	\$521,596	\$353,579
Child average income	\$76,153	\$46,680
Transfers and bequests		
Any transfer during 1996-2014	48%	67%
Total transfer amount	\$9,613	\$16,751
Conditional total transfer amount	\$19,936	\$24,793
Bequests	\$2,298	\$3,562
Number of parent-kid pairs	6,444	1,595

13.2 – Age distribution during coresidency periods

	During non-coresidency periods	During periods of coresidency
Kid age distribution		
25-35	17%	30%
35-45	42%	39%
45-55	34%	27%
55-65	7%	4%
Parent age distribution		
55-65	22%	35%
65-75	49%	43%
75-85	29%	22%
Number of observations	74,984	5,406

Notes: Never coresident with parent refers to not being coresident over the whole 10-waves. Ever coresident with parent refers to at least one period of coresidence with parent during 1996-2014. Dollar amounts are expressed in 2014 U\$.

TABLE 14

Probability and total amount received by coresident and non-coresident children

Dependent variable →	Probability	Transfer amount	Positive amount
Parental permanent income ($10,000s)	0.00478*** (0.001)	398.2*** (131.0)	411.5** (159.6)
Parental initial wealth ($10,000s)	0.000592*** (0.000)	89.04*** (17.1)	88.71*** (18.7)
Parental years of schooling	0.0275*** (0.003)	489.5*** (178.7)	738.3** (316.7)
Child average income ($10,000s)	-0.0227*** (0.003)	-876.4*** (151.5)	-761.7*** (254.3)
Child years of schooling	0.0154*** (0.004)	617.1*** (223.8)	743.8** (378.8)
Number of siblings	-0.0416*** (0.006)	-1468.4*** (231.0)	-2289.0*** (435.4)
Ever coresident with parent	0.126*** (0.020)	4361.6*** (1051.2)	4235.6*** (1521.6)
N	5,547	5,547	2,886
R^2	0.14	0.22	0.20

Notes: All regressions are OLS. The "ever coresident" dummy takes a value of one if the child coresides with the parent at least in one HRS wave over the 1996-2014 period. Total amount is computed aggregating transfers at the parent-kid level over 20 years of data (1996-2014). Additional control variables include parental race, and initial age; child's gender, and cohort dummies (age brackets in 1996). Standard errors clustered at the family level. Start superscripts: * $p < 0.10$, ** $p < .05$, *** $p < 0.01$.