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TESTING PARENTAL ALTRUISM: IMPLICATIONS OF A DYNAMIC MODEL

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ABSTRACT

Each year parents transfer a great deal of money to their adult children. While intuition might suggest that these transfers are altruistic and made out of concern for the well-being of the children, the fundamental prediction of the altruistic model has been decisively rejected in empirical tests. Specifically, the required derivative restriction-that an increase of one dollar in the income of the recipient, accompanied by a decrease of one dollar in the income of the donor, leads to a one dollar reduction in transfers-fails to hold. I show in this paper that in fact, this prediction *will not* hold if parents use observations on the current incomes of children to update their expectations about future incomes. This result implies that many past studies have relied on too restrictive a test, and furthermore, that our ability to distinguish empirically between altruistic and exchange behavior is severely limited. The paper also analyzes the variation in transfer behavior over time and finds substantial change across periods in recipiency status as well as strong correlation between inter vivos transfers and the transitory income of the recipient. This evidence suggest that dynamic models can provide insights into transfer behavior that are impossible to obtain in a static context.

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1 Introduction

Intergenerational transfers between family members are an important economic phenomenon, particularly those transfers from parents to children. Gale and Scholz (1994) estimate yearly flows between parents and their non-coresident children of $50 billion in 1999 dollars. Because of the magnitude of the funds involved such transfers are likely to have a substantial impact on other economic behaviors. Certainly they will affect the well-being of both donors and recipients and will have consequences for the distribution of wealth. In addition, however, familial transfers may interact with public transfers, and in doing so could alter the effectiveness of government assistance programs.

The importance of the effects in any of these dimensions depends crucially on the motivation behind the private transfers. While the relationship between motive and impact has been long recognized, only recently have data of sufficient quality to test alternative hypotheses become available. Unfortunately, despite several efforts, a consensus has not yet been reached on the most appropriate model of behavior as none of the hypothesized models appears to be consistent with observed patterns giving.

The two most prominant models of familial behavior, altruism and exchange, make very different predictions about the redistributional aspects of private transfers, and about the interaction between public and private assistance, so distinguishing between the two is of both theoretical and practical interest. In the literature, attention has centered on testing the predictions of the altruism model. This model, wherein parents care about the welfare of their children, makes strong predictions about the signs and relative magnitudes of the effects of the donors' and recipients' incomes on transfer amounts, so testing is apparently straightforward. However, while the standard altruism model is written in a *static* context with the effects of interest being changes in lifetime transfers in response to changes in *permanent* incomes, the actual data used to test the model come from a dynamic world: Researchers observe current rather than permanent income, and single period rather than lifetime transfers. As I show in this paper this difference in measurement is likely to lead to incorrect conclusions in tests of the model's validity.

Recent work testing the predictions of the altruism model in a dynamic context (Altonji, Hayashi, and Kotlikoff, 1997) has concluded that the model is inconsistent with observed data.

Specifically, a fundamental prediction of the altruism model—that conditional on transfers being made, an increase of one dollar in the income of the recipient, accompanied by a decrease of one dollar in the income of the donor, will lead to a one dollar reduction in transfers—was decisively rejected. (I will term this relationship the "derivative restriction."[1]) However, under reasonable assumptions about the formation of expectations of future income, the derivative restriction *will not* hold. Thus, caution should be used when drawing conclusions from studies that have used the restriction as a test of altruism. Furthermore, because this derivative restriction has been the sole means of differentiating between altruism and exchange regimes, my result suggests that our ability to distinguish between the two explanations of behavior may be severely limited.[2]

The model developed here assumes that the future income of a child is not known, rather the parent knows only its distribution. Observations on the child's current income in each period provide new information that is used to update the distribution of future income. Changes in this distribution affect expected future transfers, and in a dynamic programming model feed back to affect current transfers. Through this mechanism, the responsiveness of current transfers to changes in current income is reduced, causing the derivative restriction to fail.

Intuitively, consider an example wherein the arrival of a new observation on the child's income causes the parent to reduce her estimate of the child's future income and consumption. Not only will the parent wish to increase transfers in the current period, but she will also expect to increase future transfers as well. In this case the derivative of interest–the change in current transfers for a change in current income–differs from its value in the absence of updating, and the derivative restriction predicted by the static altruism model no longer holds.

Using data from the Health and Retirement Survey (HRS), the paper provides an empirical test of this dynamic framework. Specifically, I examine the relationship between current transfers and both current and lagged income of the potential recipient and find that both variables have significant explanatory power. I interpret these results as evidence that a parent's assessment of her child's future income depends on past realizations of income. This result is consistent with

[1] Altonji et al. use the term "transfer income derivatives restriction."

[2] An alternative test of the two models relies on the sign of the effect of the recipient's income on the amount of the transfer. An altruism model predicts a negative relationship while either a positive or negative relationship is consistent with exchange. An estimated positive effect can therefore be used to discount the altruism model. However, recent empirical work has consistently found a negative relationship, and thus this test has provided no distinguishing power.

the updating model introduced below. As a specification test I test the effect of future income on current transfers and find that it does not have significant explanatory power.

In exploring the implications of this dynamic framework, I also examine variability of transfers over time. In the two years for which I have data I find a significant number of changes in recipiency. In each year approximately 13 percent of children are reported to be receiving transfers, yet only 5.5 percent of the sample receives transfers in both survey years. These dynamic aspects of behavior have frequently been ignored because of data limitations,[3] yet from the empirical work presented here they appear to be an important phenomenon.

The availability of repeated observations on each child allows me to examine transfer behavior net of permanent differences across individuals. If there exist unobserved characteristics of the parent or child that are correlated with transfer behavior and with the included measures of income, then estimated derivatives from equations that ignore these effects will be biased. In a fixed effects framework I find that the effect of current income on transfer behavior is large and significantly different from zero, but is approximately 60 percent smaller than its effect in specifications that do not control for unobservable differences across children. These results indicate a strong negative correlation between transfers and the transitory income of potential recipients and also demonstrate the necessity of adequate controls for permanent income in dynamic models of transfer behavior.

The remainder of the paper is organized as follows: In section 2 I outline the standard altruism model and discuss the tests used to distinguish this model from an exchange regime. I then expand the static model to include two periods and note the conditions under which the predicted results differ. Section 3 describes the data I use in the empirical work and section 4 discusses the estimated effects of current income on transfers. A final section concludes and summarizes the results.

2 Background and Theory

I divide the theoretical discussion into two subsections. The first presents the standard altruism model and the second extends this model to two periods.

[3]Dunn (1997), and Rosenzweig and Wolpin (1994) are exceptions. These papers both use multiple waves of the NLS surveys. However, information is not available on all siblings of the (potential) recipients, so a complete understanding of the allocation within families is not possible.

2.1 The static altruism model

In the standard altruism model parents care about the well-being of their children; they receive utility from their own consumption and from the utility of their children. Following the standard specification used in Cox (1987), the utility function of a parent is written as $U_p = U_p(c_p, V(c_k))$ where c_p and c_k are the consumption of the parent and child, respectively. The consumption of the child is determined by his own income y_k and transfers from the parent T. Thus, $c_k = y_k + T$. Because this is a one-period model there is no saving.

The comparative statics of the altruism model yield two testable predictions. First, the change in transfers for a change in a child's income is negative ($\frac{\partial T}{\partial y_k} < 0$); as the child's income increases, the marginal utility of an additional dollar of consumption decreases, and the parent transfers less. This result implies that in families with more than one child, parents will make greater transfers to lower income children, in effect compensating the lower income children for their lack of resources.

The second testable implication of the altruism model is that if transfers are positive, an increase of one dollar in the child's income along with a decrease of one dollar in the parent's income, will result in a decrease of one dollar in transfers to the child. That is, $\frac{\partial T}{\partial y_k} - \frac{\partial T}{\partial w_p} = -1$ where w_p is the income of the parent. To see why the relationship holds, consider the following intuitive example. In a one-period model a parent has an income of \$200 and her child has an income of \$50. Given this initial allocation the parent chooses to transfer \$50 to her child so that the consumption of the parent is \$150 and the consumption of the child is \$100. Now suppose the parent's income were \$199 and child's income, \$51. If the parent continues to transfer \$50 to her child, the distribution of resources would be (\$149, \$101). If this allocation were preferred to a (\$150, \$100) division then the parent would have initially chosen to transfer \$51. Thus, by a revealed preference argument the parent prefers (\$150, \$100) to (\$149, \$101) and will reduce her transfer by one dollar in response to the change in incomes.

Given these straightforward predictions, empirical tests of the model have centered on the estimates of $\frac{\partial T}{\partial y_k}$ and $\frac{\partial T}{\partial w_p}$. Early work by Cox (1987) and Cox and Rank (1992) found a *positive* relationship between a child's income and the amount of a transfer, a contradiction of the negative relationship predicted by the altruism model. However, these early studies were not able to control adequately for the income of the parent. Because well-off children tend to have well-off parents, and well-off parents make greater transfers, the estimates obtained for $\frac{\partial T}{\partial y_k}$ were positively biased. More recent efforts that better control for the incomes of both the parent and child have found a strong negative relationship between the child's income and the amount of the transfer (Cox and Jappelli 1990, Dunn 1997, McGarry and Schoeni, 1995, 1997), a result consistent with the altruism model, but also with alternative models.[4] Although the sign of $\frac{\partial T}{\partial y_k}$ found by these studies is consistent with the altruism model, the magnitudes of $\frac{\partial T}{\partial y_k}$ and $\frac{\partial T}{\partial w_p}$ (where estimated) fail to satisfy the derivative restriction, with estimates of $\frac{\partial T}{\partial y_k} - \frac{\partial T}{\partial w_p}$ that are closer to 0 than to -1.

2.2 Static versus dynamic outcomes

The model outlined above is placed in a static framework. In the context of a single period model, parents know the lifetime earnings of their children, and the lifetime consumption of children is calculated directly as the sum of earnings and transfers. Parents make greater transfers to children with lower lifetime incomes and the timing of earnings and transfers is not an issue. However, in a more representative multiperiod framework, with an uncertain future, the timing of transfers becomes an important matter.

As noted by Altonji et al. (1997), absent additional constraints, if the child's permanent income is uncertain, a parent will delay transfers in order to obtain additional information and more efficiently allocate resources. Furthermore, parents who are uncertain of their own date of death or future needs will be reluctant to part with resources they themselves might need some day and prefer to postpone transfers (Davies, 1981). Acting against the postponement of transfers is the fact that children are unlikely to be able to borrow against future transfers and therefore may not be able to smooth consumption optimally across time. Even children with high lifetime incomes may be the recipients of transfers if they are temporarily liquidity constrained and unable to attain the level of consumption predicted by their permanent incomes (Cox, 1990). Thus one would expect a negative relationship between transfers and current income, and a positive relationship between transfers and indicators of liquidity constraints. However, whereas the derivative restriction holds

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

with respect to changes in *permanent* income in a static model, it is not clear that the same relationship must exist with respect to *current* income in this dynamic framework, even if children are liquidity constrained.

To illustrate the problem formally consider a simplified version of the two period model from Altonji et al. (1997).[5] Parents receive utility from their own consumption in each period c_{p_1} and c_{p_2} and from the utility of their children, $V(c_{k_1})$, and $V(c_{k_2})$ where c_{k_t} denotes the child's consumption level in period t. Ignoring interest rates and the time rate of discount, let the utility function of the parent be

$$U_p = U(c_{p_1}) + \eta V(c_{k_1}) + U(c_{p_2}) + \eta V(c_{k_2})$$

where U and V are concave functions and the child's utility is weighted by η. Following the previous literature, I assume that the parent has income w_p in period 1 and no second period income. She saves A_1 in period 1 to finance period 2 consumption and transfers. The child has income y_{k_t} in each period t, where $t = 1, 2$. Here I focus on the case in which children are liquidity constrained in period 1 and cannot borrow across periods:[6] their consumption in each period is therefore the sum of their income, y_{k_t} and received transfers, T_t. The budget constraints can therefore be written as

$$\begin{aligned} c_{p_1} &= w_p - T_1 - A_1 \\ c_{k_1} &= y_{k_1} + T_1 \\ c_{p_2} &= A_1 - T_2 \\ c_{k_2} &= y_{k_2} + T_2. \end{aligned}$$

In the first period the parent does not know her child's period 2 income, but does know its distribution, conditional on information I available in period 1, $f(y_{k_2}|I)$. The parent will maximize her utility using the expected value of second-period utility,

$$U_p = U(c_{p_1}) + \eta V(c_{k_1}) + \int [U(c_{p_2}) + \eta V(c_{k_2})] f(y_{k_2}|I)\, dy_{k_2}.$$

In the first period the parent observes y_{k_1} and w_p and chooses T_1 and c_{p_1}. In period 2 the parent then observes y_{k_2} and divides remaining resources A_1 between T_2 and c_{p_2}.

[5] This discussion, and the notation used here draws directly on Altonji et al. (1997).

[6] As demonstrated by Altonji et al. (1997) if a child is not liquidity constrained the parent has no incentive to make transfers in the first period. The more interesting case is therefore the one in which the child does face these liquidity.

The solution to this dynamic programming model can be obtained by first solving for the optimal allocation in period 2 as a function of A_1 and y_{k_2}. That is, the parent maximizes the function

$$U_2(A_1 - T_2) + \eta V_2(y_{k_2} + T_2)$$

with respect to T_2, yielding an optimal value for T_2 (and thus c_{p_2}) as a function of A_1 and y_{k_2},

$$\begin{aligned} T_2^* &= T_2(A_1, y_{k_2}) \\ c_{p_2}^* &= A_1 - T_2. \end{aligned}$$

Using this result, the first period maximization problem is then to choose A_1 and T_1 to maximize

$$U(c_{p_1}) + \eta\, V(c_{k_1}) + \int_{y_{k_2}} [\, U(A_1 - T_2(A_1, y_{k_2})) + \eta\, V(y_{k_2} + T_2(A_1, y_{k_2}))\,]\, f(y_{k_2}|I)\, dy_{k_2}$$

subject to

$$\begin{aligned} c_{p_1} &= w_p - T_1 - A_1 \\ c_{k_1} &= y_{k_1} + T_1. \end{aligned}$$

One should note that in the above maximization problem the variables w_p, y_{k_1}, and T_1, apparently always enter in pairs as either $w_p - T_1$ or $y_{k_1} + T_1$. Altonji et al. note this result and conclude from it that the derivative restriction $\frac{\partial T}{\partial y_{k_1}} - \frac{\partial T}{\partial w_p} = -1$ continues to hold provided that I does not change.[7] However, in a plausible multiperiod framework one would expect $f(y_{k_2}|I)$ to be a function of y_{k_1}, but not of $y_{k_1} + T_1$. If the distribution of second period income does depend on the observation of first period income then the derivative restriction is broken. In their theoretical discussion, Altonji et al. note that "the determinants of expected future income" need be held constant when considering the partial derivative of transfers with respect to current income. Their empirical analysis attempts to hold constant these determinants by including measures of permanent income carefully constructed from repeated observations on income and other covariates. However, it is likely that changes in current income also change expected future income (and

[7] To understand how this conclusion is reached, consider the first order conditions of the above utility maximization problem. These equations will be functions of $w_p - T_1$ and $y_{k_1} + T_1$. Writing one such equation as $H(w_p - T_1, y_{k_1} + T_1)$, and differentiating first with respect to w_p and then with respect to y_{k_1} yields a system of two equations such that $H_1(1 - \frac{\partial T}{\partial w_p}) + H_2 \frac{\partial T}{\partial w_p} = 0$ and $H_1(-\frac{\partial T}{\partial y_{k_1}}) + H_2(1 + \frac{\partial T}{\partial y_{k_1}}) = 0$, where H_i is the derivative of the function G with respect to the i^{th} argument. These two equations can be combined and the terms rearranged to yield the result that $\frac{\partial T}{\partial y_{k_1}} - \frac{\partial T}{\partial w_p} = -1$.

thus expectations of permanent income). If this is the case, then an analysis of the effect of changes in current income on transfer behavior needs first to understand the relationship between changes in current and future incomes, and then to take into account this additional effect. The accuracy of our estimated effects and the correctness of the conclusions we draw from them will depend on our ability to do this.

To understand this mechanism in the context of the above model, consider the specific case where y_{k_1} and y_{k_2} have a bivariate normal distribution with means μ_1 and μ_2, variances σ_1^2 and σ_2^2, and a correlation coefficient ρ. The conditional distribution of y_{k_2} given y_{k_1} has an expected value equal to $\mu_2 + \rho\sigma_1\frac{(y_{k_1}-\mu_1)}{\sigma_2}$ and variance $(1-\rho^2)\sigma_2^2$. Thus, if ρ is positive, a low value of y_{k_1} ($y_{k_1} < \mu_1$) will reduce the child's period 1 consumption and increase the marginal utility of a transfer T_1. At the same time, a low value of y_{k_1} will shift the distribution of y_{k_2} to the left. This shift will decrease expected second period consumption of the child, increase the marginal utility of a transfer in that period, and thus increase the marginal utility of A_1. To equalize marginal utilities across arguments of the utility function, the parent will reduce c_{p_1} and increase both T_1 and A_1. Because of the change in A_1, the increase in T_1 will be less than if the distribution of y_{k_2} were unaffected.

The proof of this result for the general case is in the appendix. There I show that under reasonable assumptions about the relationship between income in the two periods, the value of $\frac{\partial T}{\partial y_{k_1}} - \frac{\partial T}{\partial w_p}$ lies between zero and negative one, consistent with the results of previous empirical studies. In the specific case of the bivariate normal distribution I show that the distance between $\frac{\partial T}{\partial y_{k_1}} - \frac{\partial T}{\partial w_p}$ and -1 depends directly on the magnitude of the correlation coefficient. If $\rho = 0$, so that period 1 income is uninformative about period 2 income, the derivative restriction holds.

In the empirical work that follows I use repeated observations on the income of a child to test the validity of this dynamic framework.

3 Data

The data used in this study are from the Health and Retirement Survey (HRS). The HRS is a panel survey of the U.S. population born between 1931 and 1941 and their spouses. When appropriately weighted the sample is representative of the U.S. population of the target cohort. The initial wave of questioning was conducted in 1992 with 12,652 respondents interviewed in 7703 families. The second wave followed in 1994. The follow-up rate in wave 2 was 92 percent with 11,492 respondents re-interviewed in wave 2 and 132 respondents dropped from the survey for administrative reasons. I use data on the 6626 families for whom I have information in both surveys.[8]

These data are uniquely suited to a study of transfer behavior for several reasons. First, individuals in this age group are particular likely to be making inter vivos transfers (Schoeni, 1993). Second, the survey has specific questions about transfers to children which likely result in more complete reporting of such transfers than the more general questions about assistance to individuals outside the household used in most surveys. Finally, there is relatively detailed information on each child in the family allowing for a complete within-family analysis, and two observations per child allowing for an examination of changes in transfers over time.

The families in my sample have a total of 21,170 children. The income of children plays a central role in my study; however, income is not reported for coresident children, so I exclude these children from the analysis. In addition, in order to avoid including legally required support payments, I further restrict my sample to children aged 18 and over in the first wave of the survey. With these selection criteria I have a sample of 5381 families with 16,177 children.

The means for several of the variables used in the subsequent analyses are presented in table 1. The family income of children is measured categorically in the HRS with the categories being income of less than \$10,000, \$10,000-\$25,000 and greater than \$25,000.[9] As is apparent from comparing the distribution across categories in wave 1 and wave 2, there was a significant increase in the mean income of children. Fourteen percent of children had family income of less than \$10,000 in wave 1 compared with just 8 percent in wave 2. This result is to be expected given the average age of the children and the typical age-earnings profile. It is also consistent with the slight increase in the proportion of children who are married, from 0.63 to 0.65 percent, and the accompanying income of a spouse. Along with the increase in income, the proportion owning a home increases from 0.47 to 0.52.

[8]The wave 2 data I use is from an early release. Transfer information for 166 families (2.4 percent) remains incomplete at this time. These are predominantly families that have had some significant event between waves that makes coding of the family data difficult (e.g. the death of a child, a remarriage of the parents with the complication of added step-children). This omission is not worrisome as the responsiveness of parental transfers to changes in the child's income is perhaps best understood by excluding those with significant changes in other respects that may distract from the income effect.

[9]In wave 2 the "greater than \$25,000" category was further divided into greater or less than \$40,000. I combine these two upper-most categories for consistency with the first wave.

The probability that a child receives a transfer increases substantially between waves from 0.15 to 0.19. This change is largely an artifact of the survey design. In the first wave of the survey, respondents were asked if they made a transfer of $500 or more to a child in the past year, and if so, the amount transferred. In the second wave, the cut-off for reporting transfers was lowered to $100 and the fraction of children who reportedly received a transfer increased. Consistent with the inclusion of smaller transfer amounts, the mean amount of the transfer (over positive values) decreases from $2962 to $2098. If I impose the wave 1 criterion on the wave 2 data, and treat all transfers below $500 as a zero transfer, the proportion receiving transfers in wave 2 falls to 0.13 and the average amount increases to $3024.[10] For the remainder of the paper I will use this selected sample of wave 2 transfers. The results of the multivariate analyses are unchanged when transfers of less than $500 are included.

The cross-sectional transfer patterns in wave 1 are described in detail in McGarry and Schoeni (1995) and are not repeated here. Instead I emphasize a comparison between the two waves. As shown in table 2 there is considerable variation in the receipt of transfers from wave to wave. Fifty-nine percent of children who received a transfer in wave 1 did not in wave 2 (7.7/13.2), and 55 percent of those who received a transfer in wave 2 had not received one in wave 1 (6.6/12.1). Just over 5 percent of the children in my sample received a transfer in both waves. For those who received a transfer in both waves the correlation between the two amounts is 0.19 (not shown).

Even within families there is a significant amount of re-ordering of transfer amounts. If children are ranked by the size of the transfer they receive in wave 1 and again in wave 2, the correlation between the rankings is positive, but is just 0.29.

Table 3 shows the number of children with decreased, constant, or increased income between waves, along with the direction of change of the transfer amount. Those who did not receive a transfer in either wave are excluded from the table.[11] For children whose income decreased between waves (and who had a non-zero transfer in at least one wave), the majority (58 percent) had an increase in transfers while 39 percent had a decline in transfer amounts. The relationship is

[10] Despite the fact that the survey question in wave 1 asked respondents to report only transfers of $500 or more, a few respondents reported transfers of amount less than $500. When I restrict the wave 2 transfers to those of $500 or more, I impose the same restriction on the wave 1 data. Thus, the mean amount for wave 1 increases slightly as a result of the restriction.

[11] If individuals who never received a transfer were included, and treated as receiving identical transfers (of zero) in each wave, the middle column of the table becomes (616, 5552, 2044).

even stronger for those children with an increase in income; 61 percent had a decrease in transfer amounts and 35 percent had an increase. Because the income categories are rather broad there is likely to be a good deal of movement within category that is not captured as a change in income in the data. Given the age of the children in the sample and the typical age-earnings profile, one would expect the movement within category to be positive, on average, as is the movement across categories (table 1). In accord with this hypothesis, for those with no change in income there was a somewhat greater probability of a decrease in transfers than of a increase, 55 versus 42 percent.

The numbers presented in this section indicate a substantial amount of period to period variation in recipiency, and suggest that transitory shocks to income and/or temporary liquidity constraints likely play important roles in explaining observed behavior. This evidence demonstrates the importance of studying transfers in a dynamic context. In the following section I focus directly on the relationship between the current income of children and their receipt of transfers.

4 Empirical Analysis of Income Derivatives

This section presents estimated regression equations for the probability and amount of a transfer. The goal of this exercise is to obtain an unbiased estimate of the responsiveness of transfers to changes in current income. Most past studies have not controlled for unobserved heterogeneity in transfer behavior, and have therefore likely obtained biased estimates of the effect of income. An estimate of the derivative of transfers with respect to income is important for estimating the potential degree of crowding out of private assistance by public programs. The larger the change in familial transfers for a change in the income of the potential recipient, the less effective will be government assistance programs targeting these same individuals.

In what follows I first discuss the importance of correctly specifying the error process and then present estimates of the effect of changes in the child's current income on transfers, under varying assumptions about the error terms in the equations. I do not directly test the derivative restriction in part because the use of categorical measures for the child's income in the HRS precludes an accurate test, but mainly because the theoretical analysis above and the subsequent evidence of income updating, nullifies the use of the derivative restriction as a test of altruism.

4.1 Specification of the empirical transfer equation

Omitted variables: An important consideration in the empirical analysis of transfer behavior is the correct specification of the error process. One would expect there to be differences across families in affection and other unobservables that would be correlated with transfer behavior. Even within families it is likely to be the case that there are unobserved differences across children, perhaps in ability or in the effort they apply to their jobs, that will be correlated with the parent's decision. If these factors are ignored, estimates of the included effects will be biased.

To illustrate the potential problem more formally, consider the following Stone-Geary specification of the utility function for the parent.[12]

$$U_p = (1-\eta)log(c_p - \beta_1) + \eta\, log(c_k - \beta_2).$$

In this specification β_1 and β_2 represent minimally acceptable consumption bundles for the parent and child. They are assumed to be functions of the characteristics of the specific individual and to contain any unobserved heterogeneity, where the heterogeneity may family-specific and/or child-specific. Assuming linearity, β_1 and β_2 can be written as

$$\begin{aligned} \beta_1 &= b_1 X_1 + e_1 \\ \beta_2 &= b_2 X_2 + e_2. \end{aligned}$$

This specification of the utility function implies a transfer equation of the form

$$T = \eta\, w_p - (1-\eta) y_k - \eta b_1 X_1 + (1-\eta) b_2 X_2 + \xi$$

where

$$\xi = -\eta e_1 + (1-\eta) e_2.$$

This expression is linear in e_1 and e_2—error components that may be correlated with the child's income. For example, on the family level, parents will differ in the level of consumption they desire for their children and will therefore have invested differentially in the schooling of children. These differences in schooling will in turn lead to differences in the income of the children. In this case the unobserved family specific component will be postively correlated with both current transfers and

[12]For simplicity, in this example I temporarily ignore the dynamic aspect of transfer behavior.

with the child's income. On the child level, e_2 may include a measure of the child's industriousness. If parents are satisfied with a lower level of consumption for less industrious children (i.e. β_2 is lower for these children) then ceteris paribus transfers and industriousness will be positively correlated. We would also expect the child's income to be positively correlated with his industriousness, leading again to biased effects of the derivative. Proper estimation of the transfer equation thus needs to control for these sources of potential correlation.

Permanent income: While transfers in a dynamic model are, in part, a function of permanent income, in empirical applications there is likely to be substantial measurement error in y_p. This measurement error provides additional cause for concern about the quality of the estimated coefficients in a regression analysis. Most studies of transfer behavior do not have information on the permanent income of the children and use schooling level as a proxy variable (Cox 1987, Cox and Rank 1992). If the omitted components of permanent income, such as ability, are correlated with current income, and with transfers, the estimated effects of current income are likely to be biased. Even for those studies wherein authors are able to construct measures of permanent income (Cox 1990, Altonji et al. 1992b, 1997, Dunn 1997), the measures are likely to contain a good deal of error. It is difficult to imagine that the econometrician has sufficient information to predict permanent income with the same level of accuracy achieved by parents contemplating transfers to their children. Studies that ignore these potential correlations and errors in variables likely estimate biased effects of the included variables. Below I use a fixed effect analysis to control for permanent differences across children.

4.2 Multivariate analyses

In this section I estimate equations for the probability a child receives a transfer and for the amount of the transfer. I first estimate the pair of equations in a simple cross-section specification. These specifications offer a description of transfer behavior in the cross section and provide a base against which to compare later models that control for unobserved heterogeneity. I then control for the possibility that parental decisions on transfers may differ across families in unobserved ways that are correlated with the regressors. Similar results have been reported elsewhere (McGarry and Schoeni, 1995) so I do not discuss them in detail. Extending this line of estimation, I take advantage of the multiple observations per child to control for unobserved differences across children, such as permanent income or ability, that are potentially correlated with the explanatory variables. Controlling for family fixed effects in the cross-section requires multiple observations per family, while child fixed effects require two observations per child. In order to keep the sample approximately constant across specifications, before proceeding I delete all children in one-child families and all children who are observed in only one wave (a total of 1062).[13]

4.2.1 Cross-section results

Table 4 reports the estimates for OLS specifications for the probability a child receives a transfer[14] and for the amount, as well as for family fixed-effect and child fixed-effect versions of these models. Observations for the two waves are stacked for the first two pairs of equations, but the results are substantially unchanged if I estimate equations separately for each wave.[15] The specifications control for the child's age, sex, schooling level, whether he is still in school, works full-time, is married, has children of his own, and lives within 10 miles of his parents, and characteristics of the parent(s): age, race, income, wealth, schooling, and health status. Parental characteristics that are constant over time are not identified in the family or child fixed-effect specifications in columns 3 through 6.

The estimates in the first two columns indicate that both the probability of receiving a transfer and the amount are strongly negatively related to the child's current income. Children in the lowest income category have a 8.6 percentage point greater probability of receiving a transfer than those in the highest category relative to a mean sample probability of 12 percent. The expected amount of a transfer for those in the lowest income category is $284 greater than for those in the highest with a mean amount of transfers being $319. Although the difference in amounts between the lowest and highest income brackets is significantly different from zero at a one percent level, it is small in economic terms. The change in the child's family income from the lowest (less than $10,000) to the highest (greater than $25,000) income category represents a change of at least $15,000. This

[13]The results in the first set of regressions are unchanged if these children are included in the estimation.

[14]I report estimates from a linear probability model for ease of interpretation, but logit and fixed effect (conditional) logit specifications yield identical conclusions.

[15]An F-test on the equation for the amount of the transfer fails to reject the null hypothesis that the coefficients are equal across years. A dummy variable indicating a wave 2 observation is included in the regressions but is significantly different from zero at a 5 percent level only in column 1. Standard errors in columns 1 and 2 are corrected for repeated observations per individual.

difference implies a decrease of less than 2 cents in transfers for each dollar increase in the child's income.

4.2.2 Family fixed effects

The second pair of columns reports the estimates for the family fixed-effects specifications. The unobserved family component captures differences in what families consider a minimum level of consumption.[16]

Perhaps surprisingly, most of the coefficients for the family fixed effects model are similar to the first set of estimates. The probability that a child in the lowest income category receives a transfer is 9.1 percentage points higher than a children in highest bracket, similar to the 8.6 percentage point difference in column 1. Similarly, moving from the lowest to the highest category decreases the expected value of a transfer by $229 compared to $284 in column 2. The coefficient for the middle income category also changes only slightly, from $150 to $129.

What does change significantly between specifications is the coefficient on highest grade completed. In the initial specification, schooling level and transfers were positively correlated with each additional year being associated with a $41 increase in transfers. The mean transfer (including zeros) is $319 so a change of $41 per year of schooling implies that a college graduate receives an amount in excess of 50 percent of the mean transfer beyond what a high school graduate would receive. When unobserved characteristics of the family are controlled for, the coefficient estimate falls to $14 and is not significantly different from zero at a 5 percent level. Apparently there are differences across families in transfer behavior that are correlated with schooling and not captured by the parental income, wealth and schooling variables included in the specification.[17] For instance, parents who envision a higher than average consumption level for their children invest heavily in their schooling and continue to give generous transfers. In terms of a human capital investment model one could imagine that parents who face a lower cost of capital can borrow at a sufficiently low rate that they invest more heavily in their children's schooling than might other parents, and also can afford to respond more readily to liquidity constraints encountered by the child and make

[16] Alternatively, the unobserved component could be thought of as a measure of dynastic income (Altonji, et al. 1992a). In contrast to differences in expected levels of consumption, dynastic income will change over time. If I allow the unobserved family component to vary across waves to take account of this possibility, the results are substantially unchanged.

[17] The reported results are from specifications with parental income and wealth entered in quartiles. The effects are unchanged if parental income and wealth are entered as continuous variables with linear and quadratic terms.

more transfers throughout the child's life.

4.2.3 Child-specific effects

An altruistic model predicts that parents will choose the amount to transfer over a lifetime with regard to a child's permanent income. However, if a child is unable to borrow freely across periods parents may make transfers to alleviate liquidity constraints as well. Holding current income constant, the degree to which a child is liquidity constrained depends, in part, on his permanent income. Thus transfers will be made with regard to both permanent and current incomes. The empirical specifications above do not contain a measure of permanent income of the child beyond the inclusion of completed schooling. To control for this and other permanent characteristics of the child, I estimate a fixed-effects model. Because I also control for schooling in the regression the individual specific error might best be thought of as permanent income less the effect of schooling (and other observables). If one considers permanent income to be primarily a function of schooling and ability, this unobserved error component can be termed a measure of ability.[18]

The estimated coefficients from this specification are shown in the right-most pair of columns in table 4. When child specific effects are controlled for there continues to be a significant negative relationship between a child's income and both the probability of transfer receipt and the amount, however the effect is dampened substantially from earlier estimates. Children in the lowest income category are 4 percentage points more likely to receive a transfer than children in the highest category, and the expected value of the transfer is only $145 greater, approximately 50-60 percent of the effects in the preceding columns.[19] Again assuming a $15,000 change in income across

[18]Again, because I have multiple observations per family as well as two observations per child, it is possible to estimate a "difference-in-difference" specification rather than a simple fixed-effect version, and thereby allow the family fixed effect to change over time. Thus if the transfer equations for child i in family j at time 1 and time 2 are

$$\begin{aligned} T_{ij1} &= X_{ij1}\Gamma + \theta_i + \delta_{j1} + u_{ij1} \\ T_{ij2} &= X_{ij2}\Gamma + \theta_i + \delta_{j2} + u_{ij2} \end{aligned}$$

where u_{ijt} is white noise, then both the child specific effect, θ_i, and the time varying family specific effect, δ_{jt}, can be differenced-out by examining the relationship

$$(T_{ij2} - \overline{T}_{j2}) - (T_{ij1} - \overline{T}_{j1}) = ((X_{ij2} - \overline{X}_{j2}) - (X_{ij1} - \overline{X}_{j1}))\Gamma + e_{ijt}$$

where e_{ijt} is white noise, $\overline{T}_{jt}$ is the mean value of all children in family j at time t and similarly for $\overline{X}_{jt}$. The estimated coefficients for the child's income in this specification are nearly identical to those with a simple child-specific effect, although the standard errors are increased accordingly. In footnote 19 I note the estimated effects from this difference-in-difference specification.

[19]The estimated coefficients for the two income categories from a difference-in-difference specification (see footnote 19) are 0.045, and 0.024 for the probability equation and 145 and 50.4 for the amount.

categories an increase of $1 in income is associated with less than a one cent decrease in transfers.

If one assumes that current income and unobserved ability are positively correlated, the substantial change in the estimated income coefficient suggests that there is a strong negative correlation between transfers and unmeasured ability. This result is consistent with a model wherein parents invest in the schooling of more able children and provide cash transfers to those with less ability (Behrman, Pollak, and Taubman, 1982).

The set of results in table 4 also demonstrates that estimates of the effect of current income that ignore unobserved child-specific effects may be severely biased and point to the possibility of substantially overstating the potential for crowding out if unobserved heterogeneity is ignored.

4.3 The relationship to lagged income

In the two-period model described above, the observed value of a child's period 1 income alters the expected distribution of his period 2 income, and therefore affects expected second period transfers. If the model is extended to more than two periods, period 1 income will also affect expectations about income and transfers in period 3 and beyond. Because transfers made to a child in a given period, say period 2, depend on both his current (period 2) income and his expected future (period 3) income, period 1 income will continue to affect period 2 transfers even after period 2 income is observed. More generally, under these assumptions, transfers in any period will depend on both current and lagged values of income. The regressions in table 5 test this prediction.

In the first column of table 5 I estimate the probability that a child receives a transfer in wave 2 as a function of both current (wave 2) and lagged (wave 1) income. Both measures are significant predictors of transfers at a 1 percent level, and are negatively correlated with the transfer probability. However, the effect of current income is somewhat greater than the effect of lagged income. This difference is consistent with a more direct relationship between current income and liquidity constraints than between lagged income and such constraints. Increasing current income from the lowest bracket to the highest bracket results in a 8.3 percentage point decrease in the probability of a transfer. The comparable effect for lagged income is 7 percentage points.

The second column examines the determinants of the amount of the wave 2 transfer. Being in the lowest income category in the current period increases transfers by $142, while low lagged income increases transfers by $104. Both effects are significantly different from zero, although the latter effect is significant at just a 10 percent level.

An alternative explanation for the significant effects of lagged income is measurement error. Because of the use of income categories in the survey, the income of a child is necessarily measured imprecisely. An observation on lagged income may help identify where within the category a child's current income lies. If income rises smoothly over time, a child who has income below $10,000 in period 1 and between $10,000 and $25,000 in period 2 will likely have a lower actual period 2 income than a child whose income was between $10,000 and $25,000 in each period. In this case one would expect lagged income to be negatively related to transfers. Because future income has the same potential to help identify actual income as does lagged income, the two variables should have similar explanatory power in transfer equations. Thus as a further test of the updating model, I re-estimate the first two equations in table 5, but with wave 1 transfers as the dependent variable, and current (wave 1) and future (wave 2) incomes as regressors. If the effects of period 1 income in the first two columns of table 5 are due to measurement error, then future income will have an effect on current transfers that is similar to that of lagged income. However, if lagged income affects current transfers through an updating mechanism, then the effect of future income on transfers will not be significantly different from zero since it has not been observed and therefore could not be incorporated into expectations.

In the equation for the probability of a transfer, future income is a significant predictor, but its effect is much smaller than the effect of lagged income shown in column 1. Being in the lowest income category for future income increase the probability by just 3.9 percentage points, compared to the 7.0 percentage point effect of lagged income in column 1.

With respect to the amount of the transfer, wave 2 income does not have a significant effect; the standard errors are as large as the point estimates. This result is in contrast to the large and significant predictive power of wave 1 income on wave 2 transfers. This difference is consistent with the proposed model but not with a model wherein measurement error is responsible for the significance of lagged transfers.

5 Discussion and Conclusions

This paper considers the standard test of the altruism model of transfer behavior in a dynamic context. Previous studies have consistently rejected altruism as an appropriate model based on the failure of the test of the derivative restriction. I show here that if parents use the current income of their children to update their expectations about future incomes, then the derivative restriction *ought not* to hold. In fact, for reasonable distributional assumptions, the value of $\frac{\partial T}{\partial y_k} - \frac{\partial T}{\partial w_p}$ will lie between zero and negative one. This result has important consequences for our ability to distinguish between altruistic and exchange-motivated behavior.

In addition to this theoretical contribution, the paper provides a description of the dynamic aspects of transfer behavior. Using panel data I find that the amount of change in both the probability of receiving a transfer, and in the amount received, over a two year period, is large. This result suggests that a substantial fraction of transfers are made in response to short-term income fluctuations, consistent with the liquidity constraint argument of Cox (1990).

I examine this relationship further by estimating the effect of current income on transfers, net of permanent characteristics of the child. Using multiple observations per child, I control for fixed child-specific characteristics in a regression context. I find that the estimated effect of the child's current income on transfers is biased upward, in absolute value, by approximately 50 percent when permanent differences, other than schooling, are ignored. However, even when fixed characteristics are completely controlled for, there continues to be a significant negative relationship between current income and transfers. Taken together these multivariate results indicate that both permanent and current income play an important role in the determination of transfers and offer support for the view that transfers are made both in response to permanent differences in consumption and in response to liquidity constraints. This result is consistent with earlier work by Altonji et al. (1992b) and Dunn (1997) both of whom control directly for the permanent income of the child in transfer equations, and both of whom find similar effects for the two measures of income, but with the effect of permanent income consistently smaller.

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Appendix

The model in section 2.2 yields the first period maximization problem,

$$max\;\; U_1(c_{p_1}) + \eta\, V_1(c_{k_1}) + \int [\, U_2(A_1 - T_2(A_1, y_{k_2}) + \eta\, V_2(y_{k_2} + T_2(A_1, y_{k_2}))\,]\, f(y_{k_2}|I)\, dy_{k_2}$$

with respect to c_{p_1} and T_1 subject to the following constraints

$$\begin{aligned} A_1 &= w_p - c_{p_1} - T_1 \\ c_{k_1} &= y_{k_1} + T_1. \end{aligned}$$

Differentiating with respect to c_{p_1} and T_1 results in the first order conditions for an interior solution:

$$\begin{aligned} U_1' - \int [U_2'\,(1 - T_2') + \eta\, V_2'\, T_2'\,]\, f(y_{k_2}|I)\, dy_{k_2} &= 0 \\ \eta\, V_1' - \int [U_2'\,(1 - T_2') + \eta\, V_2'\, T_2'\,]\, f(y_{k_2}|I)\, dy_{k_2} &= 0 \end{aligned}$$

where primes denote derivatives and the arguments of the functions are omitted for clarity but are uniquely determined by the subscripted functions. Let

$$g' = U_2'(1 - T_2') + \eta\, V_2'\, T_2'$$

Then differentiating the first order conditions yields a system of equations

$$\begin{aligned} U_1''\, dc_{p_1} - \int [g''\,(dw_p - dc_{p_1} - dT_1)\, f(y_{k_2}|I) - g'\, f_{y_{k_1}}(y_{k_2}|I)\, dy_{k_1}]\, dy_{k_2} &= 0 \\ \eta\, V_1''\, dy_{k_1} + \eta\, V_1''\, dT_1 - \int [g''\,(dw_p - dc_{p_1} - dT_1)\, f(y_{k_2}|I) + g'\, f_{y_{k_1}}(y_{k_2}|I)\, dy_{k_1}]\, dy_{k_2} &= 0 \end{aligned}$$

where $f_{y_{k_1}}(y_{k_2}|I)$ is the derivative of the probability density function of y_{k_2} with respect to y_{k_1}.

$$\begin{aligned} \text{Let } G_1 &= \int g''\, f(y_{k_2}|I) dy_{k_2} \\ \text{and let } G_2 &= \int g'\, f_{y_{k_1}}(y_{k_2}|I)\, dy_{k_2}, \end{aligned}$$

then

$$\begin{bmatrix} U_1'' + G_1, & G_1 \\ G_1, & \eta\, V_1'' + G_1 \end{bmatrix} \begin{bmatrix} dc_{p_1} \\ dT_1 \end{bmatrix} = \begin{bmatrix} G_1\, dw_p + G_2\, dy_{k_1} \\ G_1\, dw_p + (G_2 - \eta\, V_1'')dy_{k_1} \end{bmatrix}$$

This system can be solved for $\partial T_1/\partial y_{k_1}$ and $\partial T_1/\partial w_p$.

$$\begin{aligned} \partial T_1/\partial y_{k_1} &= \frac{-U_1''\,\eta\, V_1'' + U_1''\, G_2 - G_1\,\eta\, V_1''}{\triangle} \\ \partial T_1/\partial w_p &= \frac{G_1\, U_1''}{\triangle} \end{aligned}$$

where

$$\triangle = \begin{vmatrix} U_1'' + G_1, & G_1 \\ G_1, & \eta V_1'' + G_1 \end{vmatrix}$$

and

$$\frac{\partial T_1}{\partial y_{k_1}} - \frac{\partial T_1}{\partial w_p} = -1 + \frac{U_1'' G_2}{\triangle}.$$

U_1'' is negative, $\triangle$ is positive. Thus if $G_2 < 0$ then $(U_1''G_2)/\triangle > 0$ and $-1 < \frac{\partial T_1}{\partial y_{k_1}} - \frac{\partial T_1}{\partial w_p} < 0$. The difference from -1 depends on the value of G_2.

What might one expect for G_2? Note first that g' is a marginal utility and is therefore expected to be monotonically decreasing in y_{k_2}. It can then be shown that if the effect of an increase in the child's period 1 income is to shift the distribution of y_{k_2} to the right (in other words, the random variable y_{k_2} becomes stochastically larger as y_{k_1} increases)[20] then G_2 will negative.[21]

Consider a concrete example wherein y_{k_1} and y_{k_2} are jointly normal with means μ_1 and μ_2, variances σ_1^2 and σ_2^2 and covariance $\rho\sigma_1\sigma_2$. In this case,

$$G_2 = \left(\frac{\rho}{\sigma_1(1-\rho^2)}\right) E\left[g'\left(y_{k_2} - \left(\mu_2 + \frac{\sigma_2}{\sigma_1}\rho(y_{k_1} - \mu_1)\right)\right)\right]$$

where $E[\cdot]$ denotes the expected value of $[\cdot]$. The expectation term in the above expression is the covariance of the marginal utility of period one savings and the child's second period income which is negative; an increase in the child's second period income increases the family's second period resources and lowers the marginal utility of a dollar carried over to that period. Thus, if ρ is positive, so that a greater value of y_{k_1} implies a greater expected value of y_{k_2}, then G_2 is negative. And the relationship

$$\frac{\partial T_1}{\partial y_{k_1}} - \frac{\partial T_1}{\partial w_p} > -1.$$

In the special case where $\rho = 0$ so that y_{k_1} is uninformative about y_{k_2}, the fraction

$$\frac{U_1'' G_2}{\triangle} = 0$$

and

$$\frac{\partial T_1}{\partial y_{k_1}} - \frac{\partial T_1}{\partial w_p} = -1.$$

[20] $y_{k_2}^*$ is stochastically larger than y_{k_2} if $F_{y_{k_2}^*}(x) < F_{y_{k_1}}(x)\ \forall\, x$ (Bickel and Doksum, 1977).

[21] The derivation also requires that y_{k_2} be bounded to lie between 0 and some maximum income W.

Table 1
Means of Selected Variables for Sample of Children
n=16,177

	Wave 1		Wave 2	
	Mean	Std Err	Mean	Std Err
Total Family Income:				
less than $10,000	0.14	0.002	0.08	0.002
$10,000-25,000	0.30	0.004	0.21	0.003
greater than 25,000	0.41	0.004	0.46	0.004
Demographic Variables:				
Age	30.9	0.04	32.9	0.04
Male	0.50	0.004	0.50	0.004
Owns home	0.47	0.004	0.52	0.004
Lives within 10 miles of parent	0.40	0.004	0.38	0.004
Married	0.63	0.004	0.65	0.004
Number of children	1.23	0.010	1.39	0.010
Highest grade completed	13.04	0.017	13.15	0.018
Attending school	0.07	0.002	0.05	0.002
Transfers:				
Received a transfer	0.15	0.003	0.19	0.003
Amount of (non-zero) transfers	2962	122	2098	89
Received a transfer $\geq$ $500	0.14	0.003	0.13	0.003
Amount of transfer $\geq$ $500	3055	126	3024	129

* Number of observations differs for some variables due to missing values. Sample is children 18 and over who do not live with their parents and for whom information is available in each wave.

Table 2
Number[†] and (Percent) Receiving Transfers in Each Year

	Year 2 status		
Year 1 status	received transfer	no transfer	total
received transfer	882 (5.5)	1237 (7.7)	2119 (13.2)
no transfer	1065 (6.6)	12930 (80.2)	13995 (86.8)
total	1947 (12.1)	14167 (87.9)	16114 (100.0)

[†] Sample size differs from table 1 due to missing observations on transfer receipt.

Table 3
Relationship between Change in Income and Change in Transfers

	Change in Transfer Amount			
Change in Income	decreased	no change	increased	total†
decreased				
number	77	8	115	200
percent	38.5	4	57.5	100
same				
number	745	45	578	1368
percent	54.5	3.3	42.3	100
increased				
number	336	20	195	551
percent	61	3.6	35.4	100

† Rows may not sum to 100 due to rounding.
Sample is children receiving a transfer in at least one wave.

Table 4
Effects of Child's Characteristics on the Probability and Amount of a Transfer

	OLS		Family F.E.		Child F.E.	
	(1)	(2)	(3)	(4)	(5)	(6)
	Prob	Amount	Prob	Amount	Prob	Amount
Total Family Income						
Less than $10,000	0.086	284.3	0.091	229.0	0.039	145.4
	(0.009)	(48.1)	(0.008)	(46.2)	(0.011)	(72.5)
10,000-24,999	0.069	149.6	0.066	128.8	0.025	58.1
	(0.006)	(32.6)	(0.005)	(31.6)	(0.008)	(50.3)
25,000 or more (omitted)	–	–	–	–	–	–
	–	–	–	–	–	–
Years of schooling	0.006	40.7	-0.000	14.4	0.008	46.5
	(0.001)	(6.8)	(0.001)	(7.8)	(0.005)	(33.2)
Own a home	-0.021	27.1	-0.016	18.2	0.032	183.7
	(0.006)	(30.7)	(0.005)	(29.0)	(0.010)	(69.2)
Married	-0.021	-67.9	-0.022	-65.4	-0.045	-132.4
	(0.006)	(32.5)	(0.005)	(29.3)	(0.011)	(73.1)
Num children less than 18	0.009	7.6	0.011	16.9	0.008	-9.2
	(0.002)	(8.9)	(0.002)	(10.6)	(0.005)	(35.5)
Currently in school	0.094	388	0.068	342.7	0.028	213.6
	(0.012)	(81.8)	(0.009)	(50.8)	(0.015)	(97.2)
Number of Observations	26,912	26,573	26,912	26,573	26,912	26,573

Additional child characteristics included in the regressions but not shown are: age, sex, lives within 10 miles of parent, works full-time, a dummy for income missing. Parental characteristics included but not shown are income and wealth (in quartiles), health marital status, race, age, schooling, and an indicator for wave 2. These parental variables are not identified in the family fixed effect analysis.

Table 5
OLS Estimates of the Probability and Amount of a Transfer
With lagged and future income and family fixed effects

	Wave 2 transfers with Lagged Income		Wave 1 transfers with Future Income	
	Prob	Amount	Prob	Amount
Current Income:				
Less than $10,000	0.083	142.4	0.108	351.7
	(0.012)	(63.1)	(0.012)	(65.4)
10,000-24,999	0.062	49.6	0.076	221.2
	(0.008)	(41.2)	(0.009)	(46.1)
25,000 or more (omitted)				
Lagged Income:				
Less than $10,000	0.070	104.2	–	–
	(0.011)	(56.5)	–	–
10,000-24,999	0.056	110.2	–	–
	(0.008)	(41.4)	–	–
25,000 or more (omitted)				
Future Income:				
Less than $10,000	–	–	0.039	69.8
	–	–	(0.013)	(69.7)
10,000-24,999	–	–	0.038	51.9
	–	–	(0.009)	(45.5)
25,000 or more (omitted)				
Number of Observations	13,858	13,623	13,987	13,868

Additional variables included in the regressions but not shown are: schooling, lives within 10 miles of parent, works full-time, ownsa home, currently in school, married, number of children, and a dummy for missing income.