Intergenerational Altruism and Retirement Transfers: Evidence from the Social Security Notch*

ANITA MUKHERJEE

December 19, 2020

Abstract

Old-age financial security is an important topic given increasing life expectancies and scarce resources. As the elderly navigate this new retirement landscape, their preferences (or lack thereof) for altruism towards children will play a key role in determining the intergenerational transfers of money and time. I contribute new evidence on the extent of altruistic preferences using quasi-random variation in Social Security benefits induced by an inflation-indexing mistake. I find support for pure altruism, as individuals who received extra money because of the mistake passed on about 6.75% to children via inter vivos transfers without receiving any care in return. On the contrary, children reduce caregiving monotonically with increases in parental Social Security benefits, suggesting that Social Security impacts time use among younger generations. These results have practical implications for how looming reforms in Social Security will impact an often ignored group: the children of beneficiaries.

Keywords: altruism, intergenerational transfers, Social Security, caregiving

*I am grateful for helpful comments to Gopi Shah Goda, Rob Hoyt, Nicole Maestas, Olivia S. Mitchell, Kosali Simon, and Justin Sydnor; seminar participants at UC-Irvine, the University of Wisconsin-Madison, and Florida State University; and conference participants at the 2019 AEA and the 2017 ARIA annual meetings. E-mail: anita.mukherjee@wisc.edu; Affiliation: Department of Risk and Insurance, Wisconsin School of Business, University of Wisconsin-Madison. Mailing address: 5279 Grainger Hall, 975 University Avenue, Madison, WI 53706.

1 Introduction

Late life care is one of the largest risks faced by individuals, yet this care is insufficiently insured. Most elderly people rely on a mix of formal insurance, government safety nets, and informal care to meet their needs. They also share resources of both money and time generously with children, which raises a puzzle despite decades of attention to the topic: what economic or behavioral forces explain this behavior? Are these transfers made in return for caregiving, or are they made due to purely altruistic preferences? Disentangling the types of behaviors that drive intergenerational transfers is important not only to inform behavioral theories, but also because the reasons dictate the effects of policy reforms targeted at financing retirement. For example, the effects of in-kind versus cash transfers, or reductions in Social Security benefits, will vary depending on whether recipient preferences are altruistic.

More broadly, looming reforms in Social Security warrant exploration of how they might impact different groups. The most obvious group is the beneficaries themselves, but the present analysis suggests that the children of these beneficiaries also stand to be significantly affected. The elderly poverty alleviation aspect of Social Security in some ways protects the children of beneficiaries from a baseline of caregiving both in terms of time and money. Thus, it is not surprising that changes in benefits will affect the next generation in meaningful ways.

The hypotheses regarding intergenerational transfers involve models of pure altruism, in which parents fully internalize their children's utility; impure altruism, in which parents also care about reciprocal care, e.g., caregiving; and non-altruism, in which transfers result purely from social contracts designed to fix market failures. There are also related theories, such as that proposed in Andreoni (1989), which provides a new explanation for perceived altruism—that people give away resources to children or charities out a desire to feel a "warm glow." A relatively large body of work has investigated these hypotheses and documented

an array of evidence mostly consistent with models of impure altruism. For example, in a well-known paper, Altonji, Hayashi and Kotlikoff (1997) strongly reject a model of pure altruism using data from the Panel Study of Income Dynamics.

I make three key contributions in this paper to build on the prior literature. First, I explore the extent to which public transfers are essentially "passed on" by recipients to the next generation using a new source of variation relevant to Social Security policy. This question is of great interest in public policy design and is related to longstanding theories about distributive neutrality. The main empirical innovation in this paper is to leverage variation in Social Security benefits from the Social Security Notch to study the impact of income on retirement transfers. The Notch is a frequently used instrument to study income effects because it created large and unanticipated changes in payments for individuals born between 1901 and 1916 versus those born between 1917 and 1922 due to an inflation-indexing mistake. This quasi-random experiment provides an ideal laboratory to study the role of income, especially that from Social Security benefits, on family transfers.

Second, I explore intergenerational altruism using data on both downstream (parent-to-child) and upstream (child-to-parent) financial transfers, covering both inter vivos transfers and bequests. These transfers are prevalent and substantial: in the sample I study, 19% of parents make at least some inter vivos transfers amounting to an average of $5,000 (2012 dollars) per year. The instrumental variable results show that the annual pass-through rate of Social Security benefits to the next generation is about 6.75% based on inter vivos transfers alone. The analysis does not reveal any impact of Social Security benefits on upstream transfers, though these are also less prevalent.

Third, I examine both downstream and upstream transfers of time. The reason this is important is because one of the reasons that impure altruism, or strategic altruism, may persist among generations is because some of the services valued in old age cannot be pur-

chased on the market. An example is caregiving from children. In fact, this missing market is the basic premise of the "child as old-age security" or "family constitution" models reviewed in Laferrère and Wolff (2006). The data show that overall, about 20% of children provide in-kind care to their elderly parents. Interestingly, the instrumental variable results show that children reduce caregiving proportionally with increases in parental Social Security benefits, even though they receive *more money* from their parents. There are no effects of Social Security benefits on downstream transfers of time, suggesting that altruistic preferences primarily dictate monetary transfers.

Because I find that increased Social Security benefits lead to more monetary transfers to children and reduced caregiving in return, I lend new support to models of pure altruism in explaining family transfers. Beyond informing theories about altruistic preferences, the present analysis is relevant because Social Security is important in and of itself. The program's benefits are a key source of income in old-age, with 48% of elderly married recipients and 69% of elderly unmarried recipients relying on Social Security for the majority of their income (Social Security Administration 2017). The amount of Social Security that one receives is determined by the individual's own (or spouse's) income histories, along with age of claiming benefits. The program is also large—according to the Social Security Administration, nearly one trillion dollars will be disbursed to about 63 million people in 2018. Despite the key role that Social Security plays in old-age financial security, the program is expected to face significant reform in the coming years as the trust fund from which benefit payments are made will otherwise be exhausted by 2037 (Goss 2010).

This paper proceeds as follows. In Section 2, I review the related literature, provide an overview of basic altruism models in the context of intergenerational transfers, and develop four testable hypotheses. In Section 3, I provide background on the Social Security Notch and explain how I operationalize the instrumental variable strategy. In Section 4, I discuss

the datasets used and describe the raw data patterns. In Section 5, I provide the estimation strategy, econometric results, and interpretation of findings. I then conclude in Section 6.

2 Literature Review, Altruistic Preferences, and Hypotheses

The role of altruism in family transfers has been studied extensively in economics. The earliest papers on the topic are Barro (1974), which showed that altruism led to families perfectly offsetting any government stimulus bonds with intergenerational transfers (this is the well-known and much-debated Ricardian Equivalence hypothesis), and Becker (1974), which showed that if preferences are altruistic and intergenerational transfers occur, changing the distribution of income between parents and children has no impact on their consumption or welfare. Early applications of these theories examined pay-as-you-go systems like Social Security, which rely by definition on one generation supporting another. For example, Zhang and Zhang (1998) finds that the impact of Social Security on economic growth depends on intergenerational transfers and the Social Security tax rate. There has been much work on the topic since these seminal papers, and interested readers will find helpful reviews in Laferrère and Wolff (2006) and Kolm and Ythier (2006).

2.1 Background on Intergenerational Transfers

This paper is related to several strands of literature studying family transfers. Seminal papers in this literature include McGarry (1999) and McGarry and Schoeni (1997), which show that parents exhibit meaningful variation among children in inter vivos transfers, preferring to give to those most needy, while exhibiting remarkable equality in bequests. Interestingly, the present instrumental variable results are consistent with patterns studied in McGarry and Schoeni (1997) showing that parents give money to children without reciprocal care. There are also alternate explanations for why monetary parent-to-child retirement transfers may occur. For example, Liu and Mukherjee (2018) shows that such transfers are sometimes

made strategically to "spend down" assets for the purposes of Medicaid eligibility to fund nursing home care.

Another related paper is Groneck (2017), which shows evidence for the "exchange model" as opposed to the altruism model. In that paper, the author uses exit interview data from the Health and Retirement Study to show that bequests reflect both the extensive and intensive margins of help provided by specific children. The present paper examines a different question than in Groneck (2017), however, because the focus is on altruistic preferences when parents receive extra money (instead of needing more care).

Regarding why transfers of time occur, one reason is that the giver may wish to control how the transfer is used. For example, if a child wishes to provide a parent with caregiving resources, providing hours of help instead of money ensures that the transfer is used for this purpose. There is recent empirical evidence that closely related individuals also give more when they can provide in-kind instead of monetary transfers—in a lab-in-the-field experiment in Mozambique, Batista, Silverman and Yang (2015) find this effect among people selecting resources to give to the closest person outside the household.

Other papers in this literature examine the consequences of intergenerational transfers of wealth accumulation. For example, Bolt et al. (2018) finds that downstream transfers can explain up to 20% of lifetime income conditional on parental education. A particularly related paper is Lee and Tan (2017), because it also uses variation from the Notch; this paper finds that bequest motives explain up to 40% of parental wealth accumulation. The paper also finds large effects of Social Security benefits on bequests—a finding I do not replicate with statistical significance in the present analysis, likely due to different estimation techniques (the authors estimate a structural model with richer features such as mortality risk and expenditure shocks). Similarly, Moulton (2010) uses the Notch to examine intergenerational wealth inequality. Neither Lee and Tan (2017) nor Moulton (2010) study transfers of time,

however.

Understanding the role of children in providing elderly care is important in part to understand how economic forces interact, e.g., Truskinovsky and Mommaerts (2018) show that caregiving is inversely correlated with macroeconomic conditions, but also because it has significant impacts on children's labor force outcomes as studied in Van Houtven, Coe and Skira (2013). Finally, in recent work Ge, Yang and Zhang (2018) use variation in the one-child policy in China to show that retirement saving decisions respond to the number of adult children, presumably through the channel of informal care availability.

2.2 Simple Models of Pure and Impure Altruism

Because the basic (and even complex) models of altruism have already been put forth by prior literature and are widely known, I am explicit in that I do not make any modeling innovations in this paper. Instead, purely for exposition, I reproduce in brief the two models that most closely motivate the empirical work. The notation and theoretical results in what follows is taken directly from Laferrère and Wolff (2006), which provides not only a thorough literature review on family transfers and altruism models, but also conceptual details on more than 30 of the most important models. I refer interested readers to that document for a more thorough treatment of the models I summarize below.

I begin by describing the most basic altruism model. In this model, the parent's utility function is comprised of consumption C_p—the subscript p denotes parent—as well as the child's utility function, which is a function only of the child's consumption. That is, the child is not reciprocally altruistic toward the parent. The notation for the child's utility is $V(C_k)$—the subscript k denotes the kid, or child. Thus, the parent selects consumption C_p to maximize utility given by $U(C_p, V(C_k))$.[1] In this simplified, two-generation model with one

[1]The budget constraints are given by $C_p = Y_p - T$, $C_k = Y_k + T$, and $T \geq 0$, where Y represents an exogenous income and T represents the downstream monetary transfer.

period, the derivative $U_V \in (0,1)$ captures the altruism parameter.[2] Note that because the altruism model is built into the parent's utility function, the parent can maximize expected utility and remain altruistic. Thus, the "non-standard" preference U_V is what gives rise to the behavioral component in this model. In this model, parents share resources with children until the marginal utility of consumption is equal for both groups; this gives rise to the famous "redistributive neutrality" result that underlies the idea of Ricardian Equivalence.

The simplest form of the impure altruism (or strategic transfer) models makes a minor, but consequential, modification to the utility functions described so far. Specifically, a "good" e is introduced to both the parent's and the child's utility functions. For the present context, we can think of e as child-to-parent caregiving (transfer of time). The parent's utility increases in e, but because e is costly to produce for the child, the child's utility is decreasing in e. Thus $U_e > 0$ and $V_e < 0$ and the parent's utility is given by $U(C_p, e, V(C_k, e))$. With respect to transfer amounts, the parent then selects the amount of (monetary) transfer T and good e to maximize utility. The optimal transfer will yield some effort e by the child in exchange for a monetary transfer T.

2.3 Hypotheses on the Impact of Social Security Benefits on Transfers

Testing altruism theories formally requires significant detail on the components of household utility for both parents and children. To add to the literature incrementally, I focus on four testable hypotheses in the present empirical context. First, if parents are altruistic, then an increase in Social Security benefits should be accompanied by a positive change in monetary transfers to children via either inter vivos transfers or bequests. Second, because childcare is expensive, these increased transfers can alternatively occur through a time channel by which parents provide childcare for grandchildren. Third, if the altruism is impure or

[2] Laferrère and Wolff (2006) reviews these models and their related assumptions (which begin with $U_c > 0$ and $V_c > 0$) in greater detail.

strategic, and if upstream caregiving is the good e of interest, then downstream monetary transfers should be accompanied by an increase in child-to-parent caregiving. And fourth, if parents *altruistically* give transfers of time, the empirical signature of this in the data would be the lack of changes in child-to-parent monetary transfers (i.e., the children should not be compensating their parents for the childcare provided).

3 A Natural Experiment: The Social Security Notch

The empirical contribution of this paper rests on improved identification of intergenerational transfers stemming from public monetary transfers, in this case Social Security benefits. In the study of how these benefits affect intergenerational transfers, the anticipatory and endogenous nature of the benefits poses an identification problem. For one, Social Security benefits are a function of the recipient's full earning history, which is determined by a variety of (unobserved) characteristics that are also likely to predict transfer behaviors. For example, an individual with strong preferences for spending time with family may select both a lower-paying but more flexible job and a high amount of freely given care to grandchildren. Or, an individual with mental health concerns may select both a lower-paying job and a low amount of care to grandchildren. These unobserved characteristics create a problem in inferring behavioral motivations for observed transfers, as a non-corrected estimate of the impact of Social Security benefits on intergenerational transfers may be biased.

To isolate the impact of (additional) public transfers on intergenerational transfers, I thus use variation in elderly earnings from the Social Security Notch (hereafter "the Notch"), which refers to an unintended randomization of Social Security benefits for cohorts born between 1901 and 1930. The randomization resulted from a mistake in the inflation adjustment formula by the Social Security Administration in 1972 and was fixed in 1977.

The Notch generated substantial variations in the amount of Social Security benefits

provided to individuals born between 1910 and 1921. Specifically, those born between 1910 and 1916 received significant approximately 10% additional benefits in windfalls relative to those born between 1917 and 1921; the latter group eventually received some additional money under a "special transition" formula designed to lessen the discontinuity in retirement benefits among these cohorts.[3] For those born in 1922 or after, however, the benefits were calculated according to a standard (and correct) formula.

The variation induced by the Notch has been used in a number of papers to study the impact of Social Security benefits on topics such as labor force participation (Gelber, Isen and Song 2017; Gelber, Isen and Song 2016; Krueger and Pischke 1992), retirement decisions (Coile and Gruber 2007), elderly living arrangements (Engelhardt, Gruber and Perry 2005), prescription drug use (Moran and Simon 2006), use of long-term care services (Goda, Golberstein and Grabowski 2011), and even mortality (Snyder and Evans 2006).[4]

Much of the prior work using this variation uses a binary treatment indicator (i.e., whether the individual was born in 1915 or 1916), but the present analysis is conducted at a finer level using the available data on Social Security benefits. Specifically, I can use these variables to construct the expected Social Security benefits for each cohort using the ANYPIA Social Security Calculator.[5] The advantage of this calculator is that it provides the expected benefits for each cohort using all the Social Security-related policies, e.g., including the "special transition" formulas for cohorts born between 1917 and 1921.

I follow the method in Vere (2011) closely by using the ANYPIA calculator to predict Social Security benefits. The input to this calculator is the primary beneficiary's birthyear

[3]Additional background on the Social Security Notch is available at: https://www.ssa.gov/history/notchfile1.html.

[4]The labor market impacts of Social Security have been studied perhaps most broadly, for example in Friedberg (2000) using tax discontinuities, and in Mastrobuoni (2009) using a different source of benefit variation.

[5]Available here: https://www.ssa.gov/oact/anypia/.

and cohort-specific wage history (obtained from Annual Statistical Supplements), and the calculation is done separately for each possible retirement age between 62 and 68. The predicted monthly benefit is calculated as a weighted sum of the benefits for each retirement age, which are calculated from the Health and Retirement Study data (described in the next section). An example of the ANYPIA output is provided in Figure A.1; we observe that for an individual born in 1920 who retired at age 66, the monthly benefit after rounding was $501 after accounting for some provisions for wage-indexing made in 1977. Continuing to follow the method in Vere (2011), I use Consumer Price Indices from the U.S. Bureau of Labor Statistics to convert all monetary amounts to 2012 dollars.

The empirical strategy is thus an instrumental variable analysis, estimated by the following first- and second-stage equations:

$$\textit{Social Security benefits}_i = \alpha + \beta \textit{Notch}_i + \lambda_t + \delta X_i + \eta_i, \tag{1}$$

$$\textit{Transfers}_i = \alpha_{IV} + \beta_{IV} \widehat{\textit{Social Security benefits}}_i + \delta_{IV} X_i + \lambda_{IVt} + \epsilon_i. \tag{2}$$

In these equations, the *Notch* variable is the earnings level one would expect for individual i based on his or her birthyear and cohort-specific weight of retirement claiming ages. The predicted Social Security benefits are then used in the second stage to predict a variety of intergenerational transfers captured by the variable *Transfers*. I review the covariates used in the analysis in the next section. The exclusion restriction assumption is that the predicted Social Security benefits only impact intergenerational transfers via the actual Social Security benefits, which is plausible in this setting. To give a preview of the instrument's strength, Figure 1 shows the strong correlation between predicted and actual Social Security benefits using the Notch instrument (in the formal first stage regression, the associated F-statistic turns out to be 24.23 and is discussed in Section 5).

4 Data and Descriptives

The present analysis requires first and foremost, individual-level information on birthyear (to identify those "treated" by the Notch), Social Security benefits, and intergenerational transfers. Because the Notch concerns cohorts born between 1901 and 1922, the data must also capture rich economic behaviors among these older cohorts. Two related datasets that contain all the necessary information are the Health and Retirement Study (HRS), which focuses on those aged 50 or more, combined with the Asset and Health Dynamics among the Oldest Old (AHEAD) survey, which focuses on those aged 70 or more. Since these datasets are frequently used together, I refer to them collectively as the "HRS." These surveys are nationally representative, longitudinal surveys that are conducted every two years. I use data from the 1992 through 2010 surveys as this is the timespan over which information about intergenerational transfers are available; the relevant variables are reviewed in McGarry and Schoeni (1995) and summarized below.

4.1 Sample Definition

I begin with a sample of all respondents born between 1901 and 1930. To create the analysis sample, I make a few restrictions following prior work as in Vere (2011) and Goda, Golberstein and Grabowski (2011), which also conduct instrumental variable analysis using the Notch. First, the analysis includes only primary beneficiaries; the reason for this is because the Notch affected individuals by the birthyear of the primary beneficiary, which can be identified for this sample by determining the household head.[6] Second, the analysis includes only respondents for whom the combined Social Security income within the household is at least $100 (in 2012 dollars); this is done to preserve focus on Social Security beneficiaries.

Third, and the largest restriction (60% of the observations are dropped in this step),

[6] I follow the steps in Goda, Golberstein and Grabowski (2011) to make these assignments.

the sample only includes respondents with education less than high school. The reason for this restriction is that this is the group whose income is most impacted by the Notch; since people with less than high school education obtain 71.5% of their incomes from Social Security, the variations induced by the Notch had meaningful effects among this group; prior work has also shown that the Notch instrument is mostly valid on people with low education. Finally, the sample is restricted to respondents with at least one child so that the study of intergenerational transfers is meaningful; this restriction is minor and only reduces the sample by 1.8%.

4.2 Summary Statistics

Table 1 provides summary statistics on the sample studied. There are 9,351 respondent-wave observations, and the mean level of annual Social Security benefits is $14,400 (I convert all dollar amounts reported in the survey to 2012 dollars using Consumer Price Indices). Figure 2 shows the distribution of these benefits; we observe significant variation, which is not surprising as Social Security benefits reflect lifetime income profiles. The average age in this sample is 79, and about 44% are female. Recall that since we have restricted our sample to those born between 1901 and 1930, and the earliest survey year is 1992, the sample includes people aged 62 or more. About 14% of respondents identify their race as "Black", and 11% identify their race as "Hispanic" (these are the categories of race in the survey).

Moving to the other demographic variables in Table 1, we observe that 39% of the respondents are part of a couple (as opposed to never married, widowed, or divorced/separated) and the average respondent has 3.75 children. Only about 9% of the sample reports working at the time of the survey, which is not surprising given that most respondents in this sample are beyond retirement age. Consistent with current work on long-term care insurance (e.g., Boyer et al. 2017), the prevalence of this product is relatively low at 7%. This number is also not surprising as prior work shows that prevalent upstream caregiving can dampen the

demand for long-term care insurance (Coe, Goda and Van Houtven 2015). The average wealth for each respondent is $180,000.

Next, I turn to the data on intergenerational transfers, first studied in McGarry and Schoeni (1995). The second panel of Table 1 shows summary statistics on the monetary transfers. We observe that parent-to-child inter vivos transfers are common; nearly one in five respondents reported giving their child or grandchild at least $500 in the past two years.[7] The (unconditional) average amount of transfer was $1,900; if we translate this number to the conditional amount, the average amount of transfer is $\$\frac{1,900}{0.19} = \$10{,}000$.

The HRS also asks about the probability of leaving bequests. Since these questions were not asked in the same format in all years, I report two of the available variables. The first is the probability with which the respondent plans to leave a bequest larger than $10,000[8]; nearly half (48%) of respondents indicate this to be the case. Additionally, 20% of respondents plan to bequest more than $100,000.[9] Note that the bequest variables do not specify that the money is intended for children or grandchildren, though these probabilities are highly likely to be correlated. Child-to-parent financial transfers are less prevalent; the survey reports that about 7% of respondents received such transfers, and conditional on receiving one, the amount was about $4,286 ($\$\frac{300}{0.07} = \$4{,}286$).[10]

The bottom of Table 1 shows information on the transfers of time. In the survey, parent-

[7]The survey question is: "Including help with education but not shared housing or shared food (or any deed to a house), [since R's LAST IW MONTH, YEAR/in the last two years] did you (or your [husband/wife/partner]) give financial help totaling $500 or more to [your child/any of your children] (or grandchildren)? (Definition: by financial help we mean giving money, helping pay bills, or covering specific types of costs such as those for medical care or insurance, schooling, down payment for a home, rent, etc. the financial help can be considered support, a gift or a loan.)" If the answer is yes, the amount is requested.

[8]The survey question is: "Including property and other valuables that you might own, what are the chances that you (and your [husband/wife/partner]) will leave an inheritance totaling $10,000 or more?"

[9]The survey question is: "What are the chances that you [or your (husband/wife/partner)] will leave an inheritance totaling $100,000 or more."

[10]The survey questions on child-to-parent money transfers are in the same structure as the questions on parent-to-child transfers.

to-child transfers consist of whether the respondent spent time caring for grand- or great grand-children over the past two years; the reason for this is because it is the main way in which elderly parents provide care to their children.[11] We observe that about 7% of parents spent at least some time providing childcare, and the amount of care totaled about 70.6 hours per month[12], or 17.4 hours per week. (I arrive at this calculation by dividing the unconditional average of 4.94 hours of childcare in each month by 0.07, which equals 70.6.) In the transfers of time, child-to-parent transfers are more prevalent and include any "hours of help," because the forms of caregiving can vary widely between recipients. About 20% of respondents report receiving care from their children, and the average conditional amount is about 25.8 days each month ($\frac{5.15}{0.20} = 25.8$), or 133.8 hours per month ($\frac{26.76}{0.20} = 133.8$). The question on days and hours of help are asked separately to provide a more complete picture of the frequency of caregiving.

4.3 Patterns of Intergenerational Transfers

Figure 3 shows the patterns in intergenerational transfers by Social Security benefits, and gives a preview of the formal regression results that follow. In Panel (a) of the figure, we see that the probability of any monetary parent-to-child transfer increases almost monotonically with annual Social Security benefits; a parent with benefits of $5,000 makes a transfer with probability 8%, versus nearly 30% for a parent with benefits of $25,000. As expected, the pattern persists for the amounts of money transferred from parents to children shown in Panel (b). The amounts vary from about $1,000 to $2,000 (unconditional, over the past two years) as parental Social Security benefits move from about $5,000 to $25,000.

[11] The survey question is: "Did you (or your [husband/wife/partner]) spend 100 or more hours in total [since R's LAST IW MONTH, YEAR/in the last two years] taking care of [grand or great-grandchildren/grandchildren]?" If yes, the survey then asks: "Roughly how many hours altogether did your [husband/wife/partner] spend?"

[12] The survey question is: "Roughly how many hours altogether did you(, yourself,) spend?" Note that I adjust these responses that cover two years to monthly amounts by dividing by 24.

Panels (c) and (d) of Figure 3 show patterns in child-to-parent transfers of time. We observe that the probability of providing any help to parents declines with parental Social Security benefits, despite receiving greater transfers of money along this dimension. In Panel (c), the probability of providing any help to parents declines from about 35% to 8% as parental Social Security benefits move from $5,000 to $25,000. This pattern could reveal other parental behaviors that occur as a result of increased income, such as choosing to live independently (as shown in Engelhardt, Gruber and Perry 2005) or purchasing paid home care services (as shown in Goda, Golberstein and Grabowski 2011). The decline in probability maps to a decline in the hours of care shown in Panel (d); the hours of child-to-parent help provided in the past month declines from about 70 hours to under 5 hours as parental Social Security benefits move from $5,000 to $25,000.

Figure 4 plots the pass-through rate of Social Security benefits. Interestingly, it is not the case that the pass-through rates increase with parental income; instead, the rates are about 10% both for those with annual benefits of about $5,000 or $25,000. These particular endpoints are somewhat of anomalies, however, as the pass-through rates for middle values of Social Security benefits are smaller. For example, at around the mean of $15,000 in annual benefits, the pass-through rate is about 7.5%.

5 Results and Interpretation

5.1 Analysis Outcomes

I study a variety of intergenerational transfers of money and time, using as many variables in the data as possible. For monetary parent-to-child outcomes, the outcomes are: whether the parent gave any inter-vivos transfers to a child (or grandchild) in the past two years (binary); the total amount of such inter vivos transfers (continuous); the probability with which the parent plans to bequest at least $10,000 (continuous); and the probability with

which the parent plans to bequest at least $100,000 (continuous). Monetary child-to-parent outcomes include whether any transfer was made in the past two years (binary) and the total amount of such transfers (continuous).

For the parent-to-child transfers of time, the outcomes are whether the parent provided any help to the children in the form of childcare in the past two years (binary) and the total number of hours of such care in the past month (continuous). On the child-to-parent side, there are three outcomes: whether the child provided any hours or days of help in the past two years (binary); the total number of days of such help in the past month (continuous); and the total number of hours of help in the past month (continuous).

5.2 Estimation Strategy

Since the analysis includes both binary and continuous outcomes—in many cases where the continuous outcome contains a large density of zeros—I estimate a series of IV Probit and IV Tobit models for the binary and continuous transfer outcomes, respectively. The only exception is the variables related to probabilities of bequeathing, as these are not censored; for this reason, these two outcomes are estimated via 2SLS linear regressions. The use of Probit and Tobit specifications to study inter vivos transfers has been standard in the literature (e.g., see Cox and Rank 1992; Altonji, Hayashi and Kotlikoff 1997; Schoeni 1997) with relatively few exceptions, so I follow this convention.

The IV regressions are estimated using the variables in equations (1) and (2). The covariate vector X includes a variety of covariates that are likely to predict intergenerational transfers: linear and quadratic terms for the respondent's age in years, gender (whether female), number of children, partner status (indicators for whether coupled, never married, divorced or separated, and widowed), race (indicators for whether White, Black, Hispanic, or other), and place of birth. The vector λ includes linear, quadratic, and cubed time trends, where the linear time trend is the number of years between 1990 and the survey year. In

all regressions, I use the respondent-level weights and report the coefficients as well as mean marginal effects for the nonlinear regressions. I also cluster all standard errors at the primary beneficiary birthyear, since this is the level of variation in the Notch; note that this results in only 30 clusters, making the standard errors appropriately conservative.

Note that I do not control for potentially endogenous variables such as current labor force participation, long-term care insurance, wealth, or health status; the reason is because prior work has shown these to be impacted by the Notch, and I cannot instrument for multiple endogenous variables in the regression.

5.3 Results on Monetary Transfers

I begin by reviewing the results on monetary intergenerational transfers. Table 2 shows the results on all extensive and intensive margin variables, in both parent-to-child and child-to-parent transfers. Since these are IV estimates, the first stage is shown in column (7): the variable "Predicted SS benefits" is the instrument, and the associated F-Statistic for the regression is 24.23 (well above the commonly accepted threshold of 10). The coefficient of 0.450 ($p < 0.01$) on the instrument indicates that for every \$10,000 in predicted Social Security benefits, observed Social Security benefits increase by \$4,500.

Columns (1) through (4) of Table 2 show results on parent-to-child monetary transfers. Throughout, I will provide interpretations based on the mean marginal effects for the non-linear models. The main covariate of interest is "Social Security benefits". In column (1), we observe that each \$10,000 in Social Security benefits is linked with a 7.9% ($p < 0.01$) increase in the probability of any parent-to-child inter vivos transfer. This is nearly a 42% effect size, as the baseline rate of inter vivos transfers is 19%. Note that most likely, policies that reduce Social Security benefits would not be close to \$10,000, as this would represent a nearly 70% cut for this sample. Rather, if benefits are cut by a more reasonable size of 20%, or by about \$3,000, then the coefficient implies that the likelihood of any parent-to-child

financial transfer would decline by an effect size of about 12.5% ($\frac{0.079 \times 0.30}{0.19} = 0.1249$).

The coefficient of interest in column (2) indicates that for every $10,000 in Social Security benefits, about $1,350 ($p < 0.10$) is given to children via inter vivos transfers (over two years). Since the transfer amounts are for every two years, this suggests an annual pass through rate of $675. This implied annual pass-through rate of 6.75% is non-trivial and suggests a key role of Social Security in providing benefits to the next generation. This pass-through rate could be consistent with either pure or impure altruism (i.e., 6.75% may be the rate at which the marginal utilities of consumption are equal for the two generations, as would be required by the pure altruism model), which is why I also examine transfers of time to help pin down the type of altruism most consistent with these behaviors.

Of the other covariates studied in Table 2, one that stands out is the impact of race on intergenerational money transfers. In columns (1) and (2), we observe that children of minority parents—defined as Black or Hispanic—receive significantly less financial help from their parents. Black parents provide $1,080 ($p < 0.10$) less to their children and Hispanic parents are nearly 16.1% ($p < 0.05$) less likely to provide any transfer to their children. Hispanic parents also give about $3,120 ($p < 0.01$) less. Additionally, Black parents are 19% ($p < 0.01$) percent less likely to leave a bequest greater than $10,000, and 8.4% ($p < 0.05$) less likely to leave a bequest greater than $100,000; these results are in columns (3) and (4). Yet, column (5) of Table 2 shows that Black parents are 3.6% ($p < 0.01$) more likely to receive a transfer from their children, in addition to more transfers overall (column (6)). There is no statistically significant estimate on the effect of Hispanic child-to-parent giving amounts. These patterns by race suggest that changes in Social Security benefits may disproportionately impact the financial lives of minority children with elderly parents, as they receive less help and provide more help within the family.

5.4 Results on Time Transfers

Next, we turn our attention to Table 3, which contains results on the transfers of time. I do not observe any statistically significant relationships between Social Security benefits on the extensive or intensive margins of parent-to-child time transfers, shown in columns (1) and (2), respectively. Most of the covariates are also not statistically significant, though downstream transfers of (grand)childcare increases with the number of children. It also appears that Black respondents provide more childcare; in column (1), we observe they are 3.1% ($p < 0.01$) more likely to provide childcare, and in column (2) we see that this correlates to about 4.32 additional hours per month ($p < 0.10$). There are no statistically significant patterns among Hispanic respondents.

I observe larger effects on child-to-parent transfers of time, shown in columns (3) through (5) of Table 3. In column (3), the coefficient on the variable of interest suggests that each \$10,000 in Social Security benefits is associated with about a 5.4% reduction in any help provided. This effect is large and represents a 77% effect size (though keeping in mind that this is for a \$10,000 change in benefits), as the baseline rate of any upstream time transfer is 7%. In columns (4) and (5), we observe that the \$10,000 in Social Security benefits is also associated with 1.68 fewer days of help and 9.74 fewer hours of help (each in the past month). Since Social Security benefits typically change by much less than \$10,000, the practical range of effects is smaller.

5.5 Evaluating the Hypotheses

Section 2.3 put forth four testable hypotheses to shed light on the altruistic preferences of the elderly individuals studied in this analysis. Broadly, I find support for such preferences: an increase in Social Security benefits leads to a 6.75% pass-through in inter vivos transfers to children. Note that we would not expect a 100% pass-through rate because the children in

this sample did not suffer any systematic and equally sized negative income shock; instead, altruism would suggest that the benefits are shared so that the marginal utilities of consumption are equal for parents and children. I also find that children decrease upward transfers of time in response to an increase in parental Social Security benefits, which suggests that the downward transfers of money are not strategic. I thus conclude that the empirical results are consistent with a model of pure altruism.

I do not find any evidence that parents alter downstream transfers of time, or that children alter upstream transfers of money, in response to increases in parental Social Security benefits. The lack of statistical significance on these outcomes suggests that altruistic preferences are carried out primarily by transfers of money.

5.6 Non-IV Results

The present analysis is concerned with the effects of the Notch, hence I show only the instrumental variable estimates in the main text. A strictly correlational analysis of Social Security benefits and intergenerational transfers using a wider range of data is provided in Mukherjee (2018). For comparison in this context, I provide the non-IV results in Tables A.1 and A.2. The IV and non-IV results are broadly consistent, though more coefficients are statistically significant in the non-IV estimation (as expected). In Table A.1, we observe that additional Social Security benefits are linked with greater parent-to-child inter vivos transfers and probabilities of bequeathing sizable assets, but that children (still) do not adjust financial transfers in response to parental income.

In Table A.2, all coefficients are statistically significant ($p < 0.01$); additional Social Security benefits are linked with more parent-to-child transfers of time, and less child-to-parent transfers of time. In terms of how these results inform the theoretical predictions, they only strengthen support for the altruism hypothesis since parents provide both more money and more time when receiving higher benefits, but receive less caregiving and no

change in money.

5.7 Study Limitations

I should note that this study has several limitations. One relates to the external validity of the results: since the cohort studied was born between 1901 and 1930, intergenerational transfers by these individuals may not be relevant to today's Social Security beneficiaries. Much has changed over time, including living arrangements, the expansion of formal long-term care insurance, and the availability of nursing home care. Caregiving between generations is particularly impacted by living arrangements because it requires coordination on both time and place. Yet, many patterns remain unchanged—for example, daughters remain the primary caregivers to parents, apart from spouses. Most importantly, intergenerational transfers of time and money remain prevalent (McGarry 2016; Mukherjee 2018) and if altruistic preferences are passed on between generations as documented in Scholz, Seshadri and Sicinski (2014), one can still gain valuable insights from studying prior generations.

6 Conclusion

Elderly individuals today are entering retirement with greater financial fragility (Lusardi, Mitchell and Oggero, 2018), though a silver lining is that much of the reason is due to longer and healthier lives (Eggleston and Fuchs, 2012). Still, there is great policy concern about how these golden years will be financed—pensions are severely underfunded, employers have transitioned to offering mostly defined contribution plans, and public insurance programs such as Social Security are positioned to become fiscally insolvent in less than 20 years if major changes are not made (Goss, 2010). As the current debate focuses on other margins of adjustment to help finance longer lives, such as working longer, delaying Social Security claiming, and increasing take-up of long-term care insurance, one sometimes overlooked factor is the extent to which altruistic preferences shape the way in which elderly individuals

use their scarce resources.

The present analysis uses variation in annual Social Security benefits induced by the Social Security Notch. The Notch refers to a mistake in the inflation-indexing formulas which resulted in providing some retirees with about 10% additional money in monthly benefits. Using this variation, I produce instrumental variable estimates on the impact of income windfalls on intergenerational transfers of both time and money. I find that additional Social Security benefits are linked with a net of increased monetary transfers to children and *decreases* in caregiving provided by children. The proportion of money given to the next generation is substantial: each $10,000 in additional Social Security benefits results in a 6.75% pass-through to children. This amount of additional benefit is also linked with 5.4% reduced likelihood of caregiving from children (from a baseline of 7%). These results suggest that altruistic preferences—ones that are potentially pure—play a significant role in retirement transfers.

Understanding the role of altruism in retirement transfers helps assess the broader impacts of pending Social Security reform—for example, reductions in benefits are likely to significantly harm the children of recipients as they will receive less money and need to provide more care. Alternatively, public transfers to the elderly may not be as effective as imagined because altruistic preferences will cause them to share these resources with children. Incorporating the effects of altruism can help improve the design and assessment of pending reforms related to Social Security and other policies.

References

Altonji, Joseph G., Fumio Hayashi, and Laurence J. Kotlikoff. 1997. "Parental altruism and inter vivos transfers: Theory and evidence." *Journal of Political Economy*, 105(6): 1121–1166.

Andreoni, James. 1989. "Giving with impure altruism: Applications to charity and Ricardian equivalence." *Journal of Political Economy*, 97(6): 1447–1458.

Barro, Robert J. 1974. "Are government bonds net wealth?" *Journal of Political Economy*, 82(6): 1095–1117.

Batista, Catia, Dan Silverman, and Dean Yang. 2015. "Directed giving: Evidence from an inter-household transfer experiment." *Journal of Economic Behavior & Organization*, 118: 2–21.

Becker, Gary S. 1974. "A theory of social interactions." *Journal of Political Economy*, 82(6): 1063–1093.

Bolt, Uta, Eric French, Jamie H. Maccuish, and Cormac O'Dea. 2018. "Intergenerational altruism and transfers of time and money: A life-cycle perspective." Working Paper.

Boyer, Martin, Philippe De Donder, Claude Fluet, Marie-Louise Leroux, and Pierre-Carl Michaud. 2017. "Long-term care insurance: Knowledge barriers, risk perception and adverse selection." NBER Working Paper No. 23918.

Coe, Norma B., Gopi S. Goda, and Courtney H. Van Houtven. 2015. "Family spillovers of long-term care insurance." NBER Working Paper No. 21483.

Coile, Courtney, and Jonathan Gruber. 2007. "Future Social Security entitlements and the retirement decision." *Review of Economics and Statistics*, 89(2): 234–246.

Cox, Donald, and Mark R. Rank. 1992. "Inter-vivos transfers and intergenerational exchange." *Review of Economics and Statistics*, 305–314.

Eggleston, Karen N., and Victor R. Fuchs. 2012. "The new demographic transition: Most gains in life expectancy now realized late in life." *Journal of Economic Perspectives*, 26(3): 137–56.

Engelhardt, Gary V., Jonathan Gruber, and Cynthia D. Perry. 2005. "Social Security and elderly living arrangements evidence from the Social Security Notch." *Journal of Human Resources*, 40(2): 354–372.

Friedberg, Leora. 2000. "The labor supply effects of the Social Security earnings test." *Review of Economics and Statistics*, 82(1): 48–63.

Gelber, Alexander, Adam Isen, and Jae Song. 2017. "The role of Social Security benefits in the initial increase of older women's employment: Evidence from the Social Security notch." In *Women Working Longer: Increased Employment at Older Ages*. University of Chicago Press.

Gelber, Alexander M., Adam Isen, and Jae Song. 2016. "The effect of pension income on elderly earnings: evidence from Social Security and full population data." *NBER Working Paper*.

Ge, Suqin, Dennis Tao Yang, and Junsen Zhang. 2018. "Population policies, demographic structural changes, and the Chinese household saving puzzle." *European Economic Review*, 101: 181–209.

Goda, Gopi S., Ezra Golberstein, and David C. Grabowski. 2011. "Income and the utilization of long-term care services: Evidence from the Social Security benefit notch." *Journal of Health Economics*, 30(4): 719–729.

Goss, Stephen C. 2010. "The future financial status of the Social Security program." *Social Security Bulletin*, 70: 111.

Groneck, Max. 2017. "Bequests and informal long-term care: Evidence from HRS Exit Interviews." *Journal of Human Resources*, 52(2): 531–572.

Kolm, Serge-Christophe, and Jean M. Ythier. 2006. *Handbook of the economics of giving, altruism and reciprocity: Foundations.* Vol. 1, Elsevier.

Krueger, Alan B., and Jörn-Steffen Pischke. 1992. "The Effect of Social Security on Labor Supply: A Cohort Analysis of the Notch Generation." *Journal of Labor Economics*, 10(4): 412–437.

Laferrère, Anne, and François-Charles Wolff. 2006. "Microeconomic models of family transfers." *Handbook of the Economics of Giving, Altruism and Reciprocity*, 2: 889–969.

Lee, Siha, and Kegon T. K. Tan. 2017. "Bequest motives and the Social Security Notch." Working Paper.

Liu, Junhao, and Anita Mukherjee. 2018. "Medicaid and long-term care: Do eligibility rules impact asset holdings?" Working Paper.

Lusardi, Annamaria, Olivia S. Mitchell, and Noemi Oggero. 2018. "The changing face of debt and financial fragility at older ages." *AEA Papers and Proceedings*, 108: 407–11.

Mastrobuoni, Giovanni. 2009. "Labor supply effects of the recent Social Security benefit cuts: Empirical estimates using cohort discontinuities." *Journal of Public Economics*, 93(11): 1224–1233.

McGarry, Kathleen. 1999. "Inter vivos transfers and intended bequests." *Journal of Public Economics*, 73(3): 321–351.

McGarry, Kathleen. 2016. "Dynamic aspects of family transfers." *Journal of Public Economics*, 137: 1–13.

McGarry, Kathleen, and Robert F. Schoeni. 1995. "Transfer behavior in the health and retirement study: Measurement and the redistribution of resources within the family." *Journal of Human Resources*, S184–S226.

McGarry, Kathleen, and Robert F. Schoeni. 1997. "Transfer behavior within the family: Results from the asset and health dynamics study." *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, 52(SI): 82–92.

Moran, John R., and Kosali I. Simon. 2006. "Income and the use of prescription drugs by the elderly evidence from the Notch cohorts." *Journal of Human Resources*, 41(2): 411–432.

Moulton, Jeremy G. 2010. "Chiseling a notch out of the next generation's assets: The effect of the Social Security amendments of 1972 and 1977 on intergenerational transfer behavior." Working Paper.

Mukherjee, Anita. 2018. "Time and money: Social Security benefits and intergenerational transfers." *AEA Papers and Proceedings*, 108: 396–400.

Schoeni, Robert F. 1997. "Private interhousehold transfers of money and time: New empirical evidence." *Review of Income and Wealth*, 43(4): 423–448.

Scholz, John Karl, Ananth Seshadri, and Kamil Sicinski. 2014. "Long-Run Determinants of Intergenerational Transfers." University of Michigan Retirement Research Center (MRRC) Working Paper No. 312.

Snyder, Stephen E., and William N. Evans. 2006. "The effect of income on mortality: Evidence from the Social Security Notch." *Review of Economics and Statistics*, 88(3): 482–495.

Social Security Administration. 2017. "Social Security fact sheet." Nov. Issue (Vol. 12).

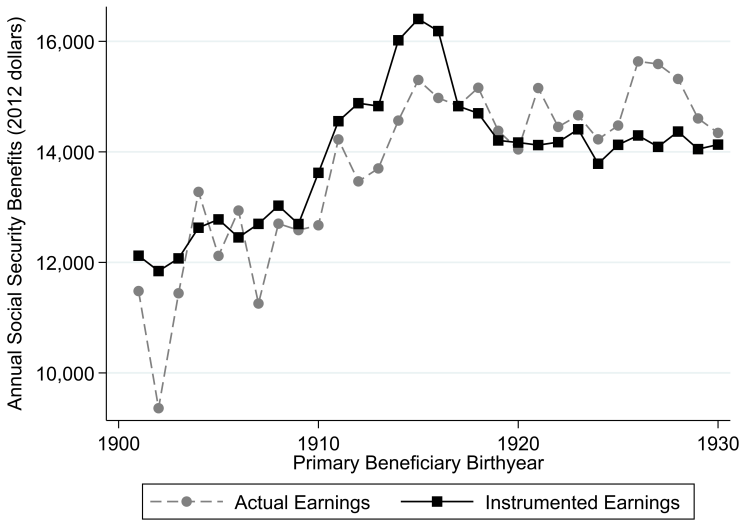
Truskinovsky, Yulya, and Corina Mommaerts. 2018. "The cyclicality of informal care." Working Paper.

Van Houtven, Courtney H., Norma B. Coe, and Meghan M. Skira. 2013. "The effect of informal care on work and wages." *Journal of Health Economics*, 32(1): 240–252.

Vere, James P. 2011. "Social Security and elderly labor supply: Evidence from the Health and Retirement Study." *Labour Economics*, 18(5): 676–686.

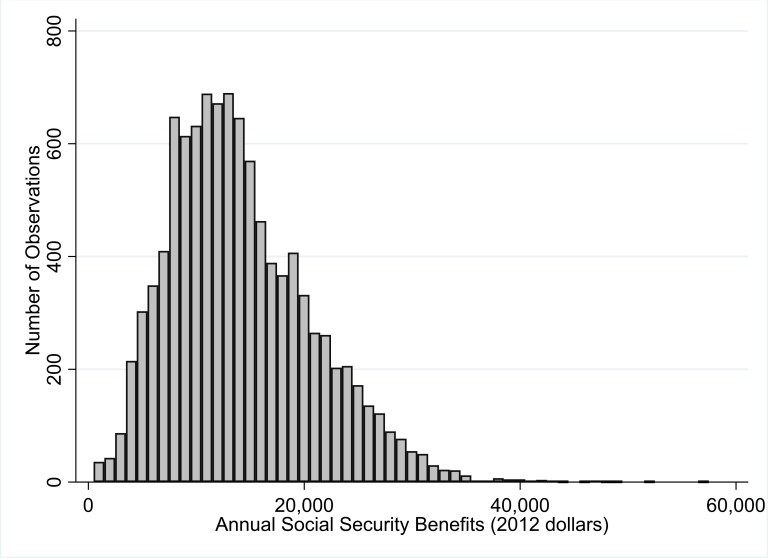
Zhang, Junsen, and Junxi Zhang. 1998. "Social Security, intergenerational transfers, and endogenous growth." *Canadian Journal of Economics*, 1225–1241.

Figure 1: Instrumented versus Actual Social Security Benefits



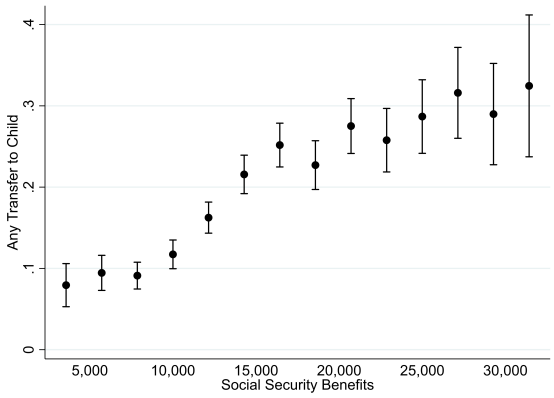
Notes: N = 9,342 respondent-wave observations. The instrumented earnings are those predicted by the Social Security Administration's ANYPIA calculator based on the respondent's birthyear, cohort-specific earnings history, and cohort-specific weighted average of retirement ages. Data source: ANYPIA estimates and HRS, 1992-2010.

Figure 2: Distribution of Annual Social Security Benefits

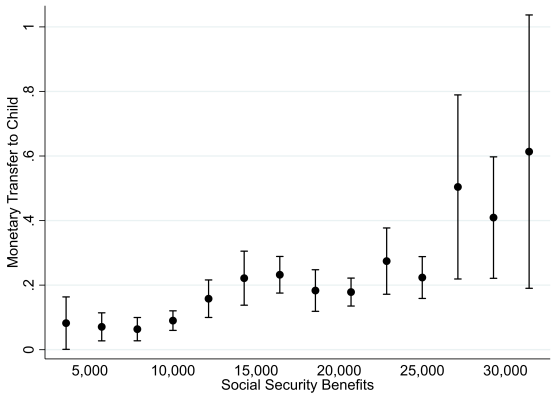


Notes: $N = 9,351$ respondent-wave observations. Data source: HRS, 1992-2010.

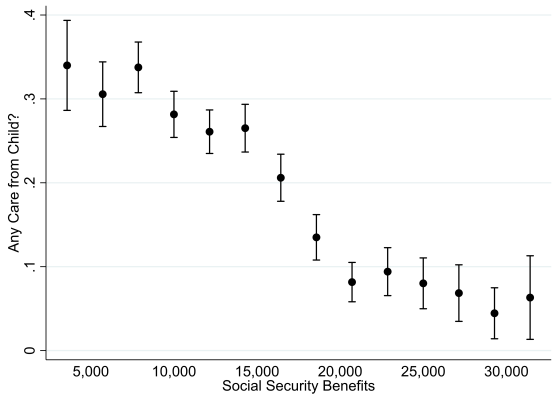
Figure 3: Patterns in Intergenerational Transfers by Social Security Benefits



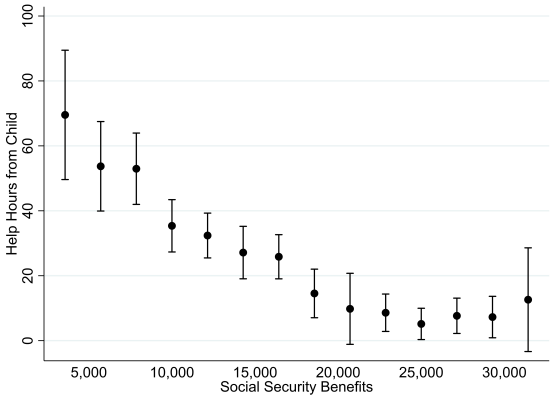
(a) Parent-to-child (any money)



(b) Parent-to-child (money amount)



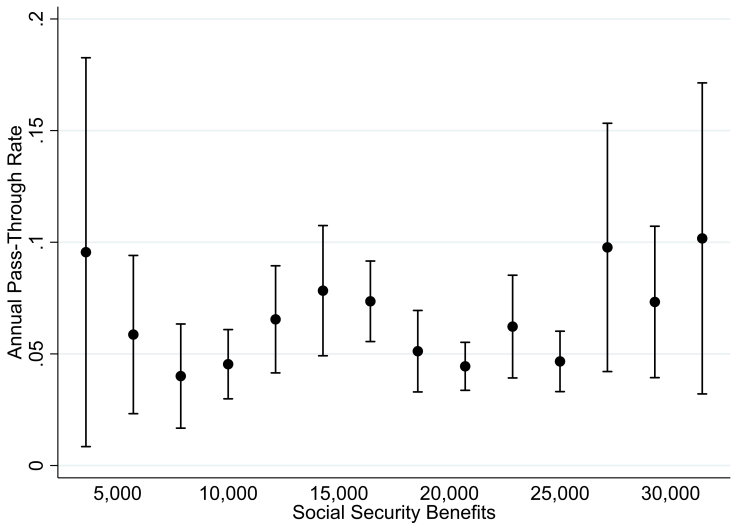
(c) Child-to-parent (any time help)



(d) Child-to-parent (hours of help)

Notes: Figure shows how various transfer variables respond to annual Social Security benefits. The dollar amounts in Panel (b) are in \$10,000. All dollar amounts are in 2012 dollars. Panel (a) shows that the probability of any monetary transfer to a child in the past two years increases with parental benefits; Panel (b) further shows that the amounts transferred to children (in the past two years) increase with parental benefits. Panel (c) shows that the probability of child-to-parent caregiving (in the past month) decreases with parental Social Security benefits; and Panel (d) shows that the hours of child-to-parent caregiving (in the past month) also decrease along this margin. $N = 9{,}351$ respondent-wave observations. Data source: HRS, 1992-2010.

Figure 4: Annual Pass-Through Rate of Social Security Benefits



Notes: The pass-through rate is the percent of annual Social Security benefits transferred annually to children via inter vivos transfers. Since the transfer amounts are reported for every two years in the survey data, I divide the amount by two to estimate an annual transfer amount. N = 9,351 respondent-wave observations. Data source: HRS, 1992-2010.

Table 1: Summary Statistics

	(1) Mean	(2) SD	(3) *N*
Respondent information and demographics			
Social Security benefits ($0000)	1.44	0.66	9,351
Age ÷ 100	0.79	0.06	9,351
Female	0.44	0.50	9,351
Race: Black	0.14	0.35	9,351
Race: Hispanic	0.11	0.31	9,351
Marital Status: Couple	0.39	0.49	9,351
Number of children	3.75	2.48	9,351
Currently working?	0.09	0.28	9,350
Has long-term care insurance?	0.07	0.25	9,141
Wealth in MN	0.18	0.35	6,319
Monetary transfers			
Parent-to-child:			
Any transfer?	0.19	0.39	9,351
Amount of transfer ($0000)	0.19	1.08	9,351
Plan to bequest > 10K?	0.48	0.45	6,865
Plan to bequest > 100K?	0.20	0.37	6,655
Child-to-parent:			
Any transfer?	0.07	0.26	9,328
Amount of transfer ($0000)	0.03	0.25	9,328
Time transfers			
Parent-to-child:			
Any transfer?	0.07	0.26	6,303
Childcare hours (1 month)	4.94	61.90	6,303
Child-to-parent:			
Any transfer?	0.20	0.40	7,521
Help days (1 month)	5.15	14.17	7,521
Help hours (1 month)	26.76	119.12	7,521

Notes: Respondent-wave level summary statistics from primary beneficiaries. Summary statistics are weighted by respondent. Social Security benefits are calculated annually, and all transfer amounts are for the past two years. Sample includes primary beneficiaries with education less than high school who were born between 1901 and 1930. Data source: HRS, 1992-2010.

Table 2: IV Results on Monetary Transfers

	Parent-to-child				Child-to-parent		First Stage
	(1) Any transfer?	(2) Amount of transfer	(3) Plan Bequest > 10K?	(4) Plan Bequest > 100K?	(5) Any transfer?	(6) Amount of transfer	(7) Social Security benefits
Social Security benefits ($0000)	0.966***	1.743*	0.183	0.050	-0.261	-0.328	
	(0.314)	(0.963)	(0.262)	(0.240)	(0.374)	(0.482)	
	[0.079]	[0.135]			[-0.010]	[-0.006]	
Female	-0.235**	-0.824***	-0.134**	-0.116**	0.390***	0.467***	-0.187***
	(0.100)	(0.257)	(0.058)	(0.051)	(0.110)	(0.150)	(0.025)
	[-0.097]	[-0.167]			[0.057]	[0.035]	
Never married	0.538	0.722	-0.057	-0.112	-0.801*	-1.012	-0.525***
	(0.447)	(1.246)	(0.222)	(0.198)	(0.483)	(0.640)	(0.110)
	[0.050]	[0.039]			[-0.094]	[-0.061]	
Divorced or Separated	0.728***	1.235	-0.043	-0.091	-0.334	-0.395	-0.475***
	(0.281)	(0.789)	(0.197)	(0.183)	(0.284)	(0.363)	(0.079)
	[0.110]	[0.132]			[-0.033]	[-0.019]	
Widowed	0.633***	1.124*	0.087	-0.022	-0.233	-0.300	-0.371***
	(0.229)	(0.653)	(0.169)	(0.156)	(0.271)	(0.335)	(0.070)
	[0.103]	[0.130]			[-0.022]	[-0.015]	
Number of children	-0.024	-0.059	-0.015**	-0.012**	0.022*	0.029*	-0.024***
	(0.015)	(0.043)	(0.007)	(0.006)	(0.013)	(0.016)	(0.005)
	[-0.011]	[-0.014]			[0.004]	[0.002]	
Black	-0.125	-0.538*	-0.190***	-0.084**	0.250***	0.285**	-0.112***
	(0.112)	(0.302)	(0.044)	(0.033)	(0.094)	(0.122)	(0.032)
	[-0.054]	[-0.108]			[0.036]	[0.022]	
Hispanic	-0.393**	-1.574***	-0.086	-0.097	-0.034	-0.096	-0.304***
	(0.168)	(0.485)	(0.083)	(0.075)	(0.178)	(0.223)	(0.035)
	[-0.161]	[-0.312]			[0.003]	[-0.002]	
Predicted SS benefits ($0000)							0.450***
							(0.091)
Model	IV Probit	IV Tobit	2SLS	2SLS	IV Probit	IV Tobit	OLS
Observations	9,342	9,342	6,863	6,653	9,319	9,319	9,342

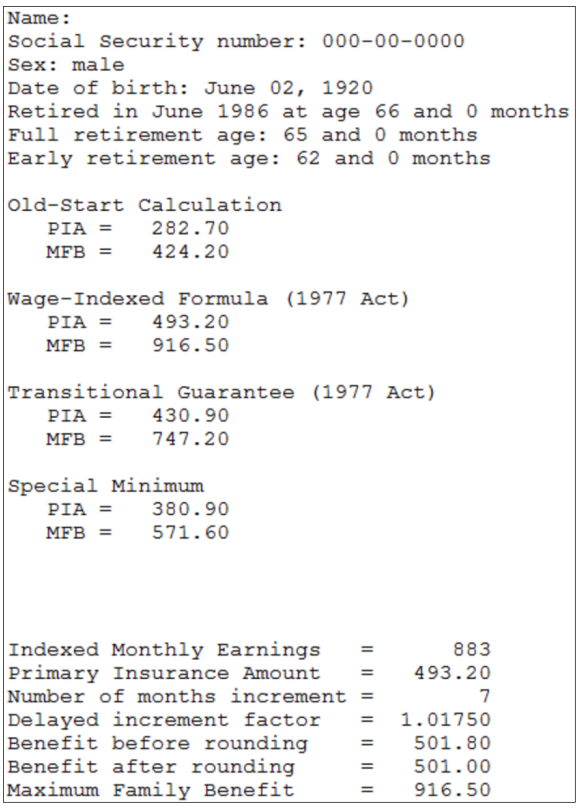
Notes: Each regression is at the respondent-wave level and is weighted by respondent. Transfer amounts in columns (2) and (6) are in $10,000. Covariates not shown: age, age squared, race-other, birthplace, and time controls (linear, quadratic, and cubic trends). Mean marginal effects are in brackets. The R-squared values for the regressions in columns (3), (4), and (5) are 0.177, 0.141, and 0.455. The F-statistic associated with column (7) is 24.23. Standard errors in parentheses are clustered at primary beneficiary birthyear. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Data source: HRS, 1992-2010.

Table 3: IV Results on Time Transfers

	Parent-to-child		Child-to-parent		
	(1) Any childcare?	(2) Hours of childcare	(3) Any help?	(4) Days of help	(5) Hours of help
Social Security benefits ($0000)	0.619	194.349	-1.016**	-47.821**	-382.633**
	(0.915)	(287.070)	(0.422)	(19.391)	(155.918)
	[0.020]	[2.774]	[-0.054]	[-1.684]	[-9.736]
Female	0.268	75.164	0.146	4.879	27.841
	(0.169)	(62.983)	(0.106)	(3.728)	(30.447)
	[0.023]	[3.081]	[0.075]	[2.314]	[14.628]
Never married	-0.121	-17.609	-0.678*	-25.915	-273.291**
	(0.809)	(225.870)	(0.385)	(18.517)	(129.590)
	[-0.050]	[-6.784]	[-0.051]	[-0.484]	[-13.514]
Divorced or Separated	-0.110	-18.270	-0.449	-22.407	-192.474
	(0.727)	(193.165)	(0.381)	(16.094)	(130.058)
	[-0.043]	[-5.948]	[-0.007]	[-0.399]	[-4.002]
Widowed	-0.006	2.515	-0.181	-8.610	-78.643
	(0.658)	(176.865)	(0.351)	(13.987)	(113.012)
	[-0.025]	[-3.737]	[0.041]	[1.518]	[9.794]
Number of children	0.043**	12.173	0.005	0.265	2.427
	(0.020)	(7.612)	(0.016)	(0.620)	(4.474)
	[0.004]	[0.532]	[0.006]	[0.228]	[1.696]
Black	0.305***	86.124*	0.002	2.572	13.904
	(0.110)	(48.790)	(0.075)	(3.310)	(28.906)
	[0.031]	[4.322]	[0.025]	[1.411]	[8.963]
Hispanic	-0.134	-24.065	-0.267	-10.015	-64.401
	(0.317)	(84.525)	(0.180)	(7.909)	(68.172)
	[-0.034]	[-4.322]	[-0.003]	[0.453]	[6.523]
Model	IV Probit	IV Tobit	IV Probit	IV Tobit	IV Tobit
Observations	6,296	6,296	7,512	7,512	7,512

Notes: Each regression is at the respondent-wave level and is weighted by respondent. Covariates not shown: age, age squared, race-other, birthplace, and time controls (linear, quadratic, and cubic trends). Mean marginal effects are in brackets. Standard errors in parentheses are clustered at primary beneficiary birthyear. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Data source: HRS, 1992-2010.

Figure A.1: Sample ANYPIA Output



```
Name:
Social Security number: 000-00-0000
Sex: male
Date of birth: June 02, 1920
Retired in June 1986 at age 66 and 0 months
Full retirement age: 65 and 0 months
Early retirement age: 62 and 0 months

Old-Start Calculation
   PIA =   282.70
   MFB =   424.20

Wage-Indexed Formula (1977 Act)
   PIA =   493.20
   MFB =   916.50

Transitional Guarantee (1977 Act)
   PIA =   430.90
   MFB =   747.20

Special Minimum
   PIA =   380.90
   MFB =   571.60



Indexed Monthly Earnings   =      883
Primary Insurance Amount   =   493.20
Number of months increment =        7
Delayed increment factor   =  1.01750
Benefit before rounding    =   501.80
Benefit after rounding     =   501.00
Maximum Family Benefit     =   916.50
```

Notes: Figure shows a sample of output regarding an individual's monthly Social Security benefit (given by the "Benefit after rounding") obtained by inputting a hypothetical individual's birthyear, earnings history, and retirement age. The advantage of using the ANYPIA calculator from the Social Security Administration is that it takes into account all legislation that would have affected the individual's benefit amount. In this example, the benefit formula applied to the individual's calculation was that from the wage-indexed formula passed in a 1977 Social Security amendment. PIA is Primary Insurance Amount and MFB is Maximum Family Benefit; note also that these amounts are not in 2012 dollars.

Table A.1: Non-IV Results on Monetary Transfers

	Parent-to-child				Child-to-parent	
	(1) Any transfer?	(2) Amount of transfer	(3) Plan Bequest > 10K?	(4) Plan Bequest > 100K?	(5) Any transfer?	(6) Amount of transfer
Social Security benefits ($0000)	0.316***	0.814***	0.150***	0.112***	-0.073	-0.091
	(0.041)	(0.181)	(0.020)	(0.014)	(0.044)	(0.057)
	[0.080]	[0.137]			[-0.010]	[-0.006]
Female	-0.381***	-0.999***	-0.140***	-0.104***	0.427***	0.511***
	(0.052)	(0.157)	(0.025)	(0.019)	(0.085)	(0.121)
	[-0.097]	[-0.167]			[0.057]	[0.035]
Never married	0.007	-0.017	-0.084	-0.060*	-0.653**	-0.823**
	(0.299)	(0.759)	(0.070)	(0.031)	(0.305)	(0.408)
	[0.002]	[-0.003]			[-0.087]	[-0.057]
Divorced or Separated	0.249**	0.549**	-0.068**	-0.043	-0.194**	-0.219*
	(0.107)	(0.261)	(0.028)	(0.029)	(0.095)	(0.125)
	[0.063]	[0.092]			[-0.026]	[-0.015]
Widowed	0.222***	0.535***	0.066***	0.018	-0.114	-0.150
	(0.058)	(0.173)	(0.021)	(0.028)	(0.097)	(0.124)
	[0.056]	[0.090]			[-0.015]	[-0.010]
Number of children	-0.042***	-0.081**	-0.016***	-0.011***	0.026***	0.035***
	(0.009)	(0.032)	(0.003)	(0.002)	(0.009)	(0.011)
	[-0.011]	[-0.014]			[0.004]	[0.002]
Black	-0.213***	-0.644***	-0.194***	-0.077***	0.272***	0.312***
	(0.080)	(0.242)	(0.030)	(0.016)	(0.076)	(0.106)
	[-0.054]	[-0.108]			[0.036]	[0.022]
Hispanic	-0.630***	-1.854***	-0.097***	-0.077***	0.024	-0.024
	(0.088)	(0.360)	(0.024)	(0.019)	(0.122)	(0.159)
	[-0.160]	[-0.311]			[0.003]	[-0.002]
Model	Probit	Tobit	OLS	OLS	Probit	Tobit
Observations	9,342	9,342	6,863	6,653	9,319	9,319

Notes: Each regression is at the respondent-wave level and is weighted by respondent. Transfer amounts in columns (2) and (6) are in $10,000. Covariates not shown: age, age squared, race-other, birthplace, and time controls (linear, quadratic, and cubic trends). Mean marginal effects are in brackets. The R-squared values for the regressions in columns (3) and (4) are 0.179 and 0.147, respectively. Standard errors in parentheses are clustered at primary beneficiary birthyear. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Data source: HRS, 1992-2010.

Table A.2: Non-IV Results on Time Transfers

	Parent-to-child		Child-to-parent		
	(1) Any childcare?	(2) Hours of childcare	(3) Any help?	(4) Days of help	(5) Hours of help
Social Security benefits ($0000)	0.163***	45.009***	-0.230***	-8.835***	-58.872***
	(0.053)	(14.801)	(0.058)	(2.389)	(18.320)
	[0.020]	[2.809]	[-0.055]	[-1.739]	[-10.135]
Female	0.193**	49.420*	0.310***	11.638***	83.934***
	(0.086)	(28.499)	(0.061)	(2.233)	(18.203)
	[0.023]	[3.084]	[0.075]	[2.291]	[14.449]
Never married	-0.529	-145.756	-0.003	6.843	-1.226
	(0.352)	(117.378)	(0.179)	(9.744)	(56.159)
	[-0.064]	[-9.095]	[-0.001]	[1.347]	[-0.211]
Divorced or Separated	-0.468***	-130.464**	0.171	6.996	51.665
	(0.153)	(65.286)	(0.112)	(4.396)	(33.039)
	[-0.057]	[-8.141]	[0.041]	[1.377]	[8.894]
Widowed	-0.316**	-95.569*	0.371***	16.738***	131.863***
	(0.129)	(56.439)	(0.081)	(3.434)	(27.711)
	[-0.038]	[-5.964]	[0.089]	[3.295]	[22.700]
Number of children	0.032***	8.494***	0.026***	1.165***	9.909***
	(0.008)	(2.634)	(0.009)	(0.349)	(2.525)
	[0.004]	[0.530]	[0.006]	[0.229]	[1.706]
Black	0.259***	69.070**	0.106*	7.236***	52.677**
	(0.079)	(27.216)	(0.062)	(2.640)	(21.787)
	[0.031]	[4.310]	[0.026]	[1.424]	[9.068]
Hispanic	-0.280**	-69.120	-0.015	2.236	37.318
	(0.130)	(44.534)	(0.095)	(4.163)	(26.690)
	[-0.034]	[-4.313]	[-0.004]	[0.440]	[6.424]
Model	Probit	Tobit	Probit	Tobit	Tobit
Observations	6,296	6,296	7,512	7,512	7,512

Notes: Each regression is at the respondent-wave level and is weighted by respondent. Covariates not shown: age, age squared, race-other, birthplace, and time controls (linear, quadratic, and cubic trends). Mean marginal effects are in brackets. Standard errors in parentheses are clustered at primary beneficiary birthyear. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Data source: HRS, 1992-2010.