Formal Home Health Care, Informal Care, and Family Decision Making

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Abstract

We use the 1993 wave of the AHEAD data set to estimate a game-theoretic model of families' decisions concerning time spent caring for elderly individuals and financial transfers for home health care. The outcome is a Nash equilibrium where each family member jointly determines his or her consumption, transfers for formal care, and time allocation – informal care, market work, and leisure. We use the estimates to decompose the effects of child characteristics into wage effects, quality of care effects, and burden effects. We also simulate the effects of a broad range of policies of current interest.

Keywords: Long-term Care, Empirical Game Theory

1 Introduction

In recent decades, the elderly population has grown substantially. For example, the elderly population increased by 37% between 1990 and 2000. Demographers predict that the elderly population will reach 60 million, or 20% of the total population, by 2025 (Morrison, 1990). Furthermore, as of 2000, the oldest old population, those 85 years and older, was the second fastest growing age group in the population. People are living longer than ever before and, as they grow older, the elderly experience increasing physical and mental impairments. Although disability rates among the elderly decreased between 1982 and 1994 (Manton, Corder, and Stallard, 1997), the number of disabled elderly individuals has remained approximately constant at 5.5 million because of population aging,

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and the level of disability among those receiving long-term care has increased (Spector, et al. 1999).

Population aging has coincided with dramatic changes in long-term care arrangements. Children have become less likely to care for elderly parents, while elderly parents have become more likely to remain independent, move to nursing homes (Boersch-Supan et al., 1988; Wolf and Soldo, 1988), or receive formal care (i.e., care provided for pay) in their homes. For example, about 7% of the oldest old lived in institutions in 1940, but approximately 25% of the individuals in this age group were institutionalized in 1990 (Kotlikoff and Morris, 1990). Until recent decades, formal home health care was relatively uncommon. By 1992, 0.9 million individuals were receiving home health care (National Center for Health Statistics, 1994a, 1994b). Meanwhile the proportion of those aged 65 or older receiving long-term care from relatives other than spouses declined from 16.1% to 12.8% (National Center for Health Statistics, 1996b).

Population aging and the trends toward institutional and home health care have significant economic, social, and psychological implications. The high cost of institutional care often exhausts the resources of nursing home residents. Thus, many elderly individuals and their families rely on Medicaid to cover their long-term care expenses. Not only does nursing home care typically create a greater drain on private and public funds than does informal care (i.e., unpaid care, almost always provided by a family member), but institutionalization typically involves greater social and psychological costs for an elderly individual (Macken, 1986).

Home health care's share of health care expenditures has also increased dramatically in recent years. For example, it rose from 1% in 1980 to 2.8% in 1994 (National Center for Health Statistics, 1996a; US Dept of HHS 2000). Those receiving home health care are generally younger than those in nursing homes. Recipients of home health care are predominantly female and disproportionately black (National Center for Health Statistics, 1994a).

Despite the trends toward institutional and formal home health care, adult children remain a factor enabling elderly parents to live in the community. Researchers demonstrate that a majority of the elderly who remain in the community do so with the assistance of familial and social networks (Shanas, 1979a, 1979b, 1980; Cantor, 1983, Streib, 1983, Noelker and Wallace, 1985; Matthews and Rosner, 1988).

In this paper, we construct a model of family decision making where each member of the family chooses a level of consumption, contributions for formal care, market work, leisure, and informal care for an elderly parent. Specifically, we simulate the effect of subsidizing formal and informal care and relaxing the requirements for Medicaid qualification. We use the model to explain how various environmental and policy factors affect care decisions and the welfare of each family member. The model is an early step in developing structural models of family decision making and long-term care decisions.

2 Literature Review

Although predominantly empirical, the literature on elderly parental care offers several theoretical models. These models vary along several dimensions: whether family members share common preferences, which family members participate in the decision-making process, which types of care arrangements are considered, and whether other decisions are determined jointly with parental care decisions.

Papers in the elder care literature assumes that a single household utility function is appropriate in the context of elderly parents and their adult children. Hoerger, Picone, and Sloan (1996) have a family utility function and budget constraint.[1] The remaining models,[2] including the one presented in this study, are game-theoretic and thus involve separate utility functions for each family member.

Several of the existing theoretical models involve only one child in the decision-making process.[3] This assumption considerably simplifies modeling and estimation but obscures the dynamics within the younger generation. In practice, more than one adult child in a family may participate in the family's care decision, and adult siblings may disagree regarding the best source of care for an elderly parent. The potential disagreement among adult siblings and between adult children and elderly parents motivates the development of a game-theoretic framework where the players include the parent, spouse, and all of her[4] children. The burden associated with caregiving may generate strategic interaction among family members. For example, an adult child's provision of informal care for her father may depend on the amount of informal care provided by her siblings and by her mother. Although altruistic toward her father, the adult child may have incentive to free ride on her siblings' or her mother's informal care. Thus, her provision of informal care may depend negatively on the amount of care provided by other family members. Alternatively, in the spirit of Bernheim, Schleifer, and Summers (1985), a bequest motive could induce siblings to compete with one another for a greater share of the inheritance. Thus, an adult child's provision of informal care could depend positively on the amount of care provided by a sibling. Similarly, siblings may have incentive to free ride on one another with respect to financial transfers for formal home health care. The possibility of such strategic play suggests that a non-cooperative model may be appropriate in the context of families' caregiving decisions for the elderly.

As part of an effort to develop more realistic models of family decision mak-

[1] In Kotlikoff and Morris (1990) parent and child solve separate maximization problems if they live separately but maximize a weighted average of their individual utility functions subject to their pooled budget constraint if they live together.

[2] See Pezzin and Schone (1997, 1999), Sloan, Picone, and Hoerger (1997), Hiedemann and Stern (1999), Checkovitch and Stern (2002), and Engers and Stern (2002).

[3] Pezzin and Schone (1997, 1999) and Sloan, Picone, and Hoerger (1997) present models that apply to families of any size, but only one child plays a role in the family's care decision.

[4] Throughout the paper, we use female pronouns as the generic pronouns. This does not mean that only mothers need care or that only daughters provide care.

ing, Hiedemann and Stern (1999) (HS), Checkovitch and Stern (2002) (CS), Engers and Stern (2002) (ES) and the current study present game-theoretic models that accommodate a variable number of children and the possibility that all children play a role in care decisions. Whereas HS and ES develop and estimate stylized games that cannot be identified from one another given the available data (Engers and Stern, 2002), the current paper considers a much more standard game and equilibrium. Here each agent maximizes a relatively standard utility function in the context of a Nash equilibrium. The current paper also differs from previous work with respect to the scope of care decisions modeled. HS and ES model the decision whether to provide informal care, while CS models the quantity of informal care provided. Here we consider both of these choices – whether and how much informal care to provide – in a broader utility maximization framework. In the current model, family members make informal care decisions jointly with decisions concerning financial contributions for home health care, consumption, market work, and leisure.

Given the variety of care arrangements and the connection between care arrangements, one model cannot capture all possible aspects of a family's parental care and living arrangements. While Pezzin and Schone (1997), Sloan, Picone, and Hoerger (1997), Hiedemann and Stern (1999), Checkovitch and Stern (2002), and Engers and Stern (2002) focus on care arrangements, Hoerger, Picone, and Sloan (1996) and Pezzin and Schone (1999) model both care and living arrangements.[5] We present a model in which each family member decides how much informal and formal home health care to provide for elderly parents, taking living arrangements as given. This study is most closely related to those of Sloan, Picone, and Hoerger (1997), Pezzin and Schone (1999), and Checkovitch and Stern (2002). Pezzin and Schone (1999) jointly model living arrangements with the provision of care by the child (in this case, a daughter). Sloan, Picone, and Hoerger (1997), present a model in which the choice variables are not the type of care or living arrangement but hours of formal care and care provided by the child. Checkovitch and Stern (2002) model each child's provision of informal care. Finally, the provision of care by adult children may be determined simultaneously with their labor force behavior. As in our study, Ettner (1996) and Pezzin and Schone (1997, 1999) model labor force participation of adult children jointly with care and/or living arrangements.[6]

The econometric models in the elderly care literature are as varied as the the-

[5] In a related literature, Kotlikoff and Morris (1990) focus on living arrangements including residence in a nursing home.

[6] There are other factors which may be part of the family's care decision which are addressed in the long-term care literature. For instance, inter- or intragenerational transfers may be made as part of a family's long-term care decision. This possibility may be captured by assuming that the family pools its income (e.g., Hoerger, Picone and Sloan, 1996) or by explicitly modeling side payments among family members. Pezzin and Schone (1999) model intergenerational cash transfers jointly with caregiving, intergenerational household formation, and labor force behavior. In one of the models in Engers and Stern (2002), family members choose the long-term care alternative that maximizes their joint payoff and make any necessary side payments among themselves.

oretical models. Most papers present results based on nonstructural models.[7] But several recent papers present results based on structural models.[8] Previous studies, including HS and ES, assume there is a single care provider. With the exception of Checkovitch and Stern (2002) and this paper, existing studies focus on the role of a single child in each family as the primary caregiver and ignore the possibility of other children serving as sources of assistance.[9] However, data from the 1984 National Long-term Care Survey indicate that shared caregiving is an important phenomenon, especially in large families. Checkovitch and Stern (2002) show, for example, that over 4% of families with two children, almost 10% of families with three children, and about 16% of families with four children contain multiple caregivers. Among families where at least one child provides care, the probability that children share caregiving is almost 13% in families with two children, over 25% in families with three children, and almost 35% in families with four children. Even if each family uses a single caregiver, one cannot ignore the other children in the family. Children attempt to influence both the amount and the method of caregiving provided by their siblings. Not only are there possibilities for intersibling conflict as a result of elderly parental care provision, but a large majority of distant children report emotional support received from siblings regarding the situation of their disabled parent (Schoonover, Brody, Hoffman, and Kleban, 1988). This study differs from the previous literature in that it allows for multiple caregivers.

3 Medicaid Financing Rules

Medicaid is a joint federal/state, means-tested entitlement program that finances medical assistance to persons with low income. Federal contributions to each state vary according to a matching rule that depends on which medical services are financed by the state. Medicaid is estimated to have served 31.4 million persons in fiscal year (FY) 1992, at a combined cost of $118.8 billion, about 15% of total national health spending (Congressional Research Service, 1993, p. 1).

Eligibility for Medicaid is linked to actual or potential receipt of cash assistance under the Supplemental Security Income (SSI) program or the former Aid to Families with Dependent Children (AFDC) program. Elderly persons become eligible for SSI payments by having countable income (income less $20) and countable resources below standards set by federal law. In 1993, the year of

[7]See Wolf and Soldo (1988), Lee, Dwyer, and Coward (1990), Cutler and Sheiner (1993), Ettner (1996), Hoerger, Picone, and Sloan (1996), Boaz and Hu (1997), Diwan, Berger, and Manns (1997), Norgard and Rodgers (1997), Sloan, Picone, and Hoerger (1997), White-Means (1997), and Couch, Daly, and Wolf (1999).

[8]See Pezzin and Schone (1997, 1999), Hiedemann and Stern, 1999), Checkovitch and Stern (2002), and Engers and Stern (2002).

[9]See Frankfather, Smith, and Caro (1981), Johnson and Catalano (1981), Cantor (1983), Johnson (1983), Stoller and Earl (1983), Horowitz (1985), Barber (1989), Miller and Montgomery (1990), Stern (1994, 1995, 1996), Pezzin and Schone (1997, 1999), Hiedemann and Stern (1999), Engers and Stern (2002).

our sample, the SSI income limit was \$434 per month for individuals and \$652 per month for couples. The 1993 SSI resource limits were \$2000 for individuals and \$3000 for couples.

In designing their Medicaid programs, states must adhere to federal guidelines. Even so, variation among state programs is considerable. Byrne, Goeree, Hiedemann, and Stern (2003) provides information on the variation in rules across states. Eligibility in each state depends on the state's policies with regard to three main groups of individuals: categorically needy, medically needy, and individuals residing in medical care institutions or needing home and community-based care.

When determining Medicaid categorical eligibility, states have the option of supplementing the federal income standard. The State Supplement Payments (SSP) are made solely with state funds. The combined federal SSI and state SSP benefit becomes the effective income eligibility standard. Alternatively, states may use more restrictive eligibility standards than those for SSI if they were using those standards prior to the implementation of SSI.

Medicaid also allows states to cover individuals who are not poor by the relevant income standard but who need assistance with medical expenses. To qualify for medically needy coverage, individuals first deplete their resources to the state's standard and then continue to incur medical expenses until their income meets the level required by the state. States are permitted by federal law to establish a special income standard for persons who are residents of nursing facilities or other institutions. The special income limit may not exceed 300% of the maximum SSI benefit. In states without a medically needy program, this "300% rule" is an alternative way of providing coverage to individuals with incomes above the state's limit.

Finally, under the Section 1915c waiver program, states have the option of covering individuals needing home and community-based care services if these individuals would otherwise require institutional care covered by Medicaid. States use waiver programs to provide services to a diverse long-term care population, including the elderly. Spending for 1915c waiver services has grown dramatically since the enactment of the law in 1981. Federal and state spending increased from \$3.8 million in FY 1982 to \$1.7 billion in FY 1991 (Congressional Research Service, 1993, p. 400). Equivalently, about 13% of Medicaid long-term care spending covered home and community based care in 1991.

4 Theoretical Model

4.1 The Model

We model the provision of formal home health care and informal relative care for elderly individuals. The model (and data) allow us to distinguish between three important sources of variation in care provision across families. First, some family members may find caregiving to be burdensome. As discussed earlier, to the extent that caregiving is burdensome, family members may have incentive to free ride on one another in the provision of care. For example, an adult daughter's provision of care may depend negatively on the care provided by her sister. Second, some family members may be more proficient at providing care relative to other family members. Third, opportunity costs may vary among family members in the form of foregone earnings resulting in different choices of care provision.

Family members from two generations participate in the decision making process. Specifically, the decision makers include an elderly individual or couple and her/their children and children-in-law. Each family member has the opportunity to make financial contributions for formal home health care and to spend time providing informal care. Thus, the model accommodates the possibility of multiple caregivers. Family members make caregiving decisions as part of a broader utility maximization framework. The younger generation allocates time to market work, informal care, and leisure and money to consumption and formal care. The older generation no longer participates in the labor market and thus faces one fewer choice variable. In addition to consumption and leisure, utility depends on time spent providing or receiving informal care and on the health of the elderly individual(s). In turn, an elderly individual's health is a function of both informal and formal care as well as demographic characteristics. Preferences concerning the provision of care may vary across generations and among siblings, but married couples share a single set of preferences. The outcome is a Nash equilibrium where each family member maximizes utility subject to budget and time constraints, taking as given the other family members' behavior. Thus, each individual's or couple's provision of formal and informal care depends on the care provided by the other family members.

More technically, consider a family[10] with I adult children and one or two elderly parents. The family includes between $I+1$ and $2\,(I+1)$ adults depending on the marital status of the parent and each child. As mentioned above, we assume that married couples act as a single player; thus, there are $I+1$ players indexed by $i = 0, 1, 2, .., I$. When indexing married players, we use m and p for maternal and paternal and c and s for child and spouse. The term a_{ik} ($k = m, p$ for parents, and $k = c, s$ for children) takes the value 1 if the family includes the individual in question and 0 otherwise. For example, a_{1s} takes the value 1 if child 1 is married, and a_{1s} the value 0 if the child is unmarried. As discussed earlier, each player makes decisions about consumption X_i, contributions for formal home health care (measured in time units) H_i, leisure L_{ik}, time spent caring for the mother t_{mik} and father t_{pik} where $k = c, s$ for children and their spouses. The children also determine their market work time, but the parents no longer participate in the labor market. For the parents, t_{p0m} is care provided for the father by the mother, and t_{m0p} is the care provided for the mother by the father. At least one of t_{m0p} and t_{p0m} is zero, and, if there is only one parent, both are zero. Finally, parents do not care for themselves; hence t_{m0m} and t_{p0p} are both zero. Market work time is $1 - L_{ik} - \sum_{j \in m,p} t_{jik}$

[10] For now, we supress a family index n that will appear in the Estimation Section.

for the children and their spouses and zero for parents.

Health production functions,

$$\begin{aligned} Q_m &= a_{0p}\alpha_{m0p}\left(t_{m0p}+\gamma t_{m0p}^2\right)+\sum_{i=1}^{I}\sum_{k\in c,s}a_{ik}\alpha_{mik}\left(t_{mik}+\gamma t_{mik}^2\right) \quad (1)\\ &+\mu\sum_{i=0}^{I}H_i+Z_m,\\ Q_p &= a_{0m}\alpha_{p0m}\left(t_{p0m}+\gamma t_{p0m}^2\right)+\sum_{i=1}^{I}\sum_{k\in c,s}a_{ik}\alpha_{pik}\left(t_{pik}+\gamma t_{pik}^2\right)\\ &+\mu\sum_{i=0}^{I}H_i+Z_p, \end{aligned}$$

determines the health quality of each parent where Z_j is a linear combination of parent j's characteristics. The parameters α_{jik}, γ, and μ measure the effects of care provided by family members (informal care) and paid care (formal care) on health quality. The α_{jik} coefficients may depend on observed parent and child characteristics. The "health" terms, Q_m and Q_p, are really an aggregate measure of true health and accomodations made for health problems. It may be that informal care t and formal care H, do not directly affect true health but help the parent deal with health problems, or just make the parent happier than she otherwise would be. All of these effects are captured in equation (1) and can not be identified separately given data constraints.

The parents' utility function[11] takes the form

$$\begin{aligned} U_0 &= \beta_0+\beta_{10}\sum_{j\in m,p}a_{0j}\ln Q_j+\beta_{20}\varepsilon_{X0}\ln X_0+\sum_{k\in m,p}a_{0k}\beta_{30k}\varepsilon_{L0k}\ln L_{0k} \quad (2)\\ &+\sum_{\substack{j,k\in m,p\\ j\neq k}}a_{0k}a_{0j}\left(\beta_{4j0k+}\varepsilon_{t0jk}\right)t_{j0k}+\varepsilon_{u0}. \end{aligned}$$

Similarly, child i's utility function (for $i>0$) takes the form[12]

$$\begin{aligned} U_i &= \beta_0+\beta_{1i}\sum_{j\in m,p}a_{0j}\ln Q_j+\beta_{2i}\varepsilon_{Xi}\ln X_i+\sum_{k\in c,s}a_{ik}\beta_{3ik}\varepsilon_{Lik}\ln L_{ik} \quad (3)\\ &+\sum_{k\in c,s}\sum_{j\in m,p}a_{ik}a_{0j}\left(\beta_{4jik}+\varepsilon_{tjik}\right)t_{jik}+\varepsilon_{ui}. \end{aligned}$$

[11] In the estimation section, we will have occasion to define the utility function of each parent. We define the utility of parent j as

$$U_{0j}=\beta_{0j}+\beta_{10}\ln Q_j+\beta_{20}\varepsilon_{X0}\zeta\ln X_0+\beta_{30j}\varepsilon_{L0j}\ln L_{0j}+\left(\beta_{40jk+}\varepsilon_{t0jk}\right)t_{0jk}+\varepsilon_{u0j}$$

where $k=p$ if $j=m$ and $k=m$ if $j=p$ and $\zeta=.5$ if k is alive and $\zeta=1$ if k is not alive.

[12] The model in Bernheim, Schleifer, and Summers (1985) would imply that the utility child i receives from providing informal care depends on the amount of care provided by siblings. McGarry (1999) and Checkovich and Stern (2002) reject the implication of Bernheim, Schleifer, and Summers (1985).

The coefficients β_0, β_{1i}, β_{2i}, β_{3ik}, and β_{4jik} for $i = 0, 1, 2, .., I$ may depend on observed child and parent characteristics, and the errors ε_{Xi}, ε_{Lik}, and ε_{tjik} are functions of unobserved (to the econometrician) child and parent characteristics. All variables, including errors, are common knowledge to all family members. Each family member's utility depends positively on the parents' health as well as the family member's consumption and leisure. Thus, $\beta_{1i} \geq 0$, $\beta_{2i} \geq 0$, $\beta_{3ik} \geq 0$, $\varepsilon_{Xi} \geq 0$, and $\varepsilon_{Lik} \geq 0$ for $i = 0, 1, 2, .., I$. Each player maximizes U_i over its choices subject to budget and time constraints taking as given the decisions of the other family members. Children and their spouses face budget constraints of the form:

$$\max\left[Y_i^*, Y_i^{**}\right] \geq p_{Xi} X_i + q H_i \tag{4}$$

where p_{Xi} is the price of the consumption good, q is the price of a unit of paid care assistance purchased in the parents' state of residence,

$$Y_i^* = \sum_{k \in c,s} a_{ik} w_{ik} \left(1 - L_{ik} - \sum_{j \in m,p} t_{jik}\right) \tag{5}$$

is labor income,

$$Y_i^{**} = Y_i + s Y_i^* \tag{6}$$

is income net of a hypothetical negative income tax ($0 < s < 1$), and w_{ik} is the market wage. Y_i is outside income including government welfare payments, and the time constraint is implied by the definition of market work time. We use the structure in equations (4), (5), and (6) because there are some children with $Y_i^* = 0$. The utility function in equation (3) implies that consumption is always positive, so we need to force children's income to be positive. We use the negative income tax structure implied by equation (6) as a crude approximation of reality. We estimate Y_i and s using CPS data and allow it to vary across states.

For the parent, the budget constraint is

$$Y_0 \geq p_{X0} X_0 + q H_0 \tag{7}$$

if she is not eligible for Medicaid reimbursement of home health care expenses. If she is eligible, the budget constraint is

$$\Psi + q \min\left(\overline{H}, H_0\right) \geq p_{X0} X_0 + q H_0$$

where Ψ is the income limit and $q\overline{H}$ is the maximum reimbursable amount for home health care expenses. As discussed in Section 3, eligibility requirements and maximum reimbursable amounts vary across states. Since we know the parent's state of residence, we use the relevant policy variables in determining her budget constraint. This potentially allows us to be more precise (relative to studies using aggregate state data) about the effects of changes in Medicaid policy on families, since the impact may differ vastly by state.

The parents' time constraints are

$$1 \geq L_{0k} + t_{j0k}, \quad j,k = m,p; \quad j \neq k$$

where L_{0k} is the leisure time of parent k. This implies that $t_{j0k} = 1 - L_{0k}$ for $j,k = m,p$ and $j \neq k$. The standard nonnegativity constraints also apply: $t_{jik} \geq 0$ and $L_{0k} \geq 0$ for $k = m,p$, and $L_{ik} \geq 0$, $H_i \geq 0$, and $X_i \geq 0$ for $k = c,s$ and $i = 1,2,..,I$.

4.2 Family Equilibrium and First Order Conditions

The outcome of the game is a Nash equilibrium. The errors are functions of characteristics unobservable by the econometrician. For each child, we can solve for X_i using equation (4) to obtain

$$X_i = \frac{\max\left[Y_i^*, Y_i^{**}\right] - qH_i}{p_{Xi}}. \tag{8}$$

For the parent, using equation (7), we obtain

$$X_0 = \frac{Y_0 - qH_0}{p_{X0}}.$$

The model accommodates the possibility that family members do not contribute financial resources H_i or time for caregiving t_{jik}. Thus, for each child, the set of first order conditions (FOCs) for H_i is

$$\frac{\partial U_i}{\partial H_i} \leq 0,\ H_i \geq 0,\ \frac{\partial U_i}{\partial H_i} H_i = 0.$$

and the FOCs for t_{jik} and L_{ik} depend on H_i.

We can summarize the set of first order conditions for the children as

FOCs for Children						
Cases				FOCs		
L_{ik}	t_{jik}	Work	H_i	H_i	t_{jik}	L_{ik}
I	I	I	I	$\varepsilon_{Xi} = T_i^H$	$\varepsilon_{tjik} = T_{ijk}^{t1}(t_{jik})$	$\varepsilon_{Lik} = T_{ik}^{L1}$
I	I	I	C	$\varepsilon_{Xi} \geq T_i^H$	$\varepsilon_{tjik} = T_{ijk}^{t2}(t_{jik}, \varepsilon_{Xi})$	$\varepsilon_{Lik} = T_{ik}^{L2}(\varepsilon_{Xi})$
I	I	C	I	$\varepsilon_{Xi} = T_i^H$	$\varepsilon_{tjik} = T_{ijk}^{t3}(t_{jik}, \varepsilon_{Lik})$	$\varepsilon_{Lik} \geq T_{ik}^{L1}$
I	I	C	C	$\varepsilon_{Xi} \geq T_i^H$	$\varepsilon_{tjik} = T_{ijk}^{t3}(t_{jik}, \varepsilon_{Lik})$	$\varepsilon_{Lik} \geq T_{ik}^{L2}(\varepsilon_{Xi})$
I	C	I	I	$\varepsilon_{Xi} = T_i^H$	$\varepsilon_{tjik} \leq T_{ijk}^{t1}(0)$	$\varepsilon_{Lik} = T_{ik}^{L1}$
I	C	I	C	$\varepsilon_{Xi} \geq T_i^H$	$\varepsilon_{tjik} \leq T_{ijk}^{t2}(0, \varepsilon_{Xi})$	$\varepsilon_{Lik} = T_{ik}^{L2}(\varepsilon_{Xi})$
C	C	C	I	$\varepsilon_{Xi} = T_i^H$	$\varepsilon_{tjik} \leq T_{ijk}^{t3}(0, \varepsilon_{Lik})$	$\varepsilon_{Lik} \geq T_{ik}^{L1}$
C	C	C	C	$\varepsilon_{Xi} \geq T_i^H$	$\varepsilon_{tjik} \leq T_{ijk}^{t3}(0, \varepsilon_{Lik})$	$\varepsilon_{Lik} \geq T_{ik}^{L2}(\varepsilon_{Xi})$

where I denotes an interior solution and C denotes a corner solution with

$$\begin{aligned}
T_i^H &= \frac{\beta_{1i}\mu p_{Xi}X_i}{q\beta_{2i}}\overline{Q} \\
T_{ijk}^{t1}(t_{jik}) &= \beta_{1i}\left[\frac{s_i^* w_{ik}\mu}{q}\overline{Q} - \frac{\alpha_{jik}(1+2\gamma t_{jik})}{Q_j}\right] - \beta_{4jik} \\
T_{ijk}^{t2}(t_{jik},\varepsilon_{Xi}) &= \beta_{2i}\varepsilon_{Xi}\frac{s_i^* w_{ik}}{p_{Xi}X_i} - \beta_{1i}\frac{\alpha_{jik}(1+2\gamma t_{jik})}{Q_j} - \beta_{4jik} \\
T_{ijk}^{t3}(t_{jik},\varepsilon_{Lik}) &= \frac{\beta_{3ik}\varepsilon_{Lik}}{L_{ik}} - \frac{\beta_{1i}\alpha_{jik}(1+2\gamma t_{jik})}{Q_j} - \beta_{4jik} \\
T_{ik}^{L1} &= \frac{\beta_{1i}s_i^* w_{ik}L_{ik}\mu}{\beta_{3ik}q}\overline{Q} \\
T_{ik}^{L2}(\varepsilon_{Xi}) &= \frac{\beta_{2i}\varepsilon_{Xi}s_i^* w_{ik}L_{ik}}{\beta_{3ik}p_{Xi}X_i}
\end{aligned}$$

where

$$\overline{Q} = \sum_{j=m,p}\frac{a_{0j}}{Q_j}.$$

and

$$s_i^* = \begin{cases} 1 & \text{if } Y_i^* > Y_i^{**} \\ s & \text{if } Y_i^* = Y_i^{**} \end{cases}$$

Note that ε_{L0k} is an unnecessary error (in the sense that there is enough random variation to explain any observed event). Similarly, we can summarize the set of parent first order conditions as

FOCs for Parents			
Cases		FOCs	
t_{jik}	H_i	H_i	t_{jik}
I	I	$\varepsilon_{X0} = T_0^H$	$\varepsilon_{tj0k} = T_{0jk}^{t3}(t_{j0k},\varepsilon_{L0k})$
I	C	$\varepsilon_{X0} \geq T_0^H$	$\varepsilon_{tj0k} = T_{0jk}^{t3}(t_{j0k},\varepsilon_{L0k})$
C	I	$\varepsilon_{X0} = T_0^H$	$\varepsilon_{tj0k} \leq T_{0jk}^{t3}(0,\varepsilon_{L0k})$
C	C	$\varepsilon_{X0} \geq T_0^H$	$\varepsilon_{tj0k} \leq T_{0jk}^{t3}(0,\varepsilon_{L0k})$

with

$$\begin{aligned}
T_0^H &= \frac{\beta_{10}\mu p_{X0}X_0\overline{Q}}{\beta_{20}q} \\
T_{0jk}^{t3}(t_{j0k},\varepsilon_{L0k}) &= -\frac{\beta_{10}}{Q_j}\alpha_{j0k}(1+2\gamma t_{j0k}) + \frac{\beta_{30k}\varepsilon_{L0k}}{L_{0k}} - \beta_{4j0k}.
\end{aligned}$$

Define the set of first order conditions corresponding to solutions to FOCs as

$$\varepsilon = \varphi(\xi) \tag{9}$$

where ε is the vector or errors, ξ is the vector of endogenous variables, and $\varphi(\cdot)$ is the vector of functions implied by the first order conditions summarized above.

We can use these first order conditions to construct a likelihood contribution for each family.[13] For those elements of ξ corresponding to interior solutions, the relevant likelihood term is the density of the corresponding element of ε, and for those elements of ξ corresponding to corner solutions, the relevant likelihood term is either the distribution function or one minus the distribution function of the corresponding element of ε, depending on which side the corner is on. The set of equations in equation (9) are the first order conditions holding constant the behavior of all other family members. Thus, together the values of the errors that satisfy equation (9) are consistent with the observed Nash equilibrium.

4.3 Nonlinear Budget Set Issues

Equations (4) through (6) imply a kink in the children's budget constraints where $Y^* = Y^{**}$. One might think that this causes an endogeneity problem in the spirit of, for example, Hausman (1985). In particular, the error vector ε that solves the first order conditions depends on observed endogenous choices. Essentially, the inclusion of the Jacobian in the likelihood function below controls for this endogeneity because it corrects for the translation of reduced form equations into structural equations. Nevertheless consider two interesting cases in more detail. First consider a case such as that illustrated in Figure 1. Consider a child who chooses to be at point A. Our model would find an error vector ε consistent with point A. However, any point between B and C would be preferable. In fact, in a situation like that depicted in Figure 1, there would be no value of ε consistent with both point A and being at a global optimum because the solution to the first order conditions is unique. We need to be able to rule out such events.

We also have children at corner solutions. For these children there must be no value of the errors satisfying the inequalities in the relevant first order conditions that cause the child to move to a different segment of the budget line. The leading case for such a problem is a child providing no financial help for formal care. This implies that ε_{Xi} must be greater than equation T_i^H. One might worry that, for large enough ε_{Xi}, the value of consumption would increase, possibly causing the child to move from a budget segment with low hours of work to one with high hours of work. However, as ε_{Xi} increases, ε_{Li} can increase to keep the child (and her spouse) on the observed budget segment.

We used the estimated parameter vector (discussed later in Table 7) to measure the empirical importance of either problem. For each child in each family at an interior solution, we computed the value of ε consistent with the observed choice. For each child in each family at a corner solution, we simulated 10 values of ε consistent with the observed choice. Conditional on ε, we allowed the child to optimize over all of her choice variables. We counted the number of times that the child chose something other than the observed choice. Over the 335,700 choices made, there were no deviations between observed choices and optimal choices conditional on ε. Thus, while there may be a theoretical

[13] Aguirregabiria and Mira (2001) use a similar approach in another context.

problem caused by kinked budget sets, it is not an important problem empirically.

5 Data

For our empirical work, we use the 1993 wave of the Asset and Health Dynamics Among the Oldest Old (AHEAD) data set. AHEAD is a nationally representative longitudinal data set designed to facilitate study of Americans aged 70 or older. The emphasis on the joint dynamics of health, family characteristics, income, and wealth makes it a particularly rich source of information on family decisions regarding the care of elderly relatives. The 1993 wave of AHEAD contains only noninstitutionalized individuals. While it is desirable to have data which include nursing home residents, the primary focus of our research is on the provision of informal home health care and formal home health care. Hence, the issues we wish to address are not greatly impacted by the exclusion of nursing home residents. The AHEAD response rate is over 80%. Although AHEAD oversamples blacks, Hispanics, and Florida residents, this oversampling causes no estimation bias because our analysis treats race and residential location as exogenous.

We use 3,583 of the 6,047 households in the first wave of the survey. As shown in Table 1, we excluded households for a variety of reasons. In most cases (1,116), records were missing data on the respondent, the respondent's spouse, or the respondent's children. Households with working respondents (270) or two respondents each of whom provided care for the other (25) were dropped to reduce the complexity of the model. Only the black and white non-Hispanic groups remained large enough for our analysis.

Households included in AHEAD contain at least one respondent 70 years old or older. Many households also include spouses, some of whom are less than 70 years old. Spouses of respondents are also respondents. As a consequence of the exclusion of nursing home residents from the 1993 wave and the inclusion of spouses regardless of age, the characteristics of our sample deviate from those of a representative individual who is 70 years old or older. The characteristics of the respondents in the our sample are shown in Table 2. On average, the male respondents (37% of the sample) are 76.7 years old with 11.7 years of education and 2.1 living children. Seventy-two percent are married, and 93% are white. On average, the female respondents are 76.3 years old with 11.8 years of education and 2.0 living children. Forty-two percent are married, and 90% are white.

Twenty-two percent of men and 31% of women reported difficulty with an activity of daily living (ADL). The most common difficulty was walking across a room, reported by 17% of male respondents and 24% of female respondents. Thirteen percent of women and 8% of men reported difficulty bathing themselves, and prevalence rates for difficulty dressing were 12% among women and 10% among men. All other ADLs had prevalence rates of less than 10%. Twenty-eight percent of women and 24% of men reported difficulty with an instrumental activity of daily living, most frequently difficulty with walking several blocks, pulling and lifting heavy objects, climbing stairs, or driving. The fraction of households reporting (paid or unpaid) help with an ADL or IADL in our sample is 37%. Of those households, 30% paid for care in the month prior to the interview. The average amount paid per week among those paying for care is \$94. In the empirical work, contributions for home health care are measured in hours; the payment per week is divided by the cost per hour.

The survey asks each parent whether or not she is happy. Seventy-nine percent of parents reported being "happy." We use the responses to this question to help identify some of the parameters in our structural model. This is discussed in more detail later.

Our measure of parental income includes income from major government transfer programs (e.g., Social Security, SSI, Food Stamps) and other nonwage income such as veteran's benefits, retirement income, annuities, IRA distributions and income from stocks and bonds. A small number of respondents report positive wage earnings which we ignore so that we can avoid modeling the labor force behavior of the respondent. The average income of parent households in our sample is \$417 per week. Most respondents were covered by Medicare and received assistance from the Supplemental Security Income program. Because the data do not include residents of nursing homes, few respondents reported eligibility for Medicaid.

Table 3 contains information on the children of the respondents. Forty-nine percent of the children are male, and 69.8% are married. The average child is 47.0 years old with 14.0 years of education and two children. To model the decision-making process of the adult children of the elderly individuals, we need information on the market wages of the children, which is not part of the AHEAD survey. We impute wages using the Current Population Survey by regressing log-wages on demographic characteristics of the children available in AHEAD. Our estimates are reported in Table 4. The average imputed wage is \$452 per week. We also construct a measure of the leisure time consumed by the children and the respondents by treating time not spent working or caring for the parents as leisure.[14]

As indicated in Table 3, respondents and their children experience a variety of living arrangements. Over half (55%) of respondents live with a spouse or an unmarried partner. Almost one fourth (23%) of respondent households include additional members; among these additional household members, 77% are children of the respondents. However, almost all children (94%) reside outside of the respondent's household, and two thirds (66%) of these children live more than 10 miles away.

Care arrangements also vary considerably across families. Table 5 displays patterns of caregiving in our sample. Overall 22% of elderly individuals receive formal and/or informal care in their homes. Among those receiving some type

[14] We also observe whether the child lives with the parent, lives within ten miles of the parent, or lives further than 10 miles from the parent. However, work such as Stern (1995) shows that marginal distance affects caregiving decisions only at greater distances. Thus, we do not use distance as a child characteristic.

of care, 18% receive formal care, 90% receive informal care, and 8% receive both formal and informal care. Overall 6% of unmarried, childless respondents and 38% of married, childless respondents receive care in their homes. Regardless of the number of children, roughly one fourth of elderly parents receive some type of care. Among families providing some type of care, the provision of informal care depends positively and the provision of formal care depends negatively on the number of adult children.

Among elderly individuals receiving informal care, 63% receive care from their spouses, 42% receive care from their children, and 5% percent receive care from both their spouses and at least one of their children. Conditional on the receipt of informal care from at least one family member, the likelihood that the spouse and at least one adult child share informal caregiving responsibilities ranges from 3% of those with one child to 9% of those with five children. A more common type of shared caregiving involves two or more adult children. Among families with at least one informal care provider and at least two adult children, 14% include multiple caregivers among the younger generation. Not surprisingly, the likelihood that siblings share caregiving responsibilities depends positively on family size. Conditional on the receipt of informal care from at least one family member, 10% of elderly individuals with two children receive care from both children, while 17, 19, and 23% of elderly individuals with three, four, and five children, respectively, receive care from more than one child.

Among families where elderly individuals receive formal home health care, 9% of elderly parents receive financial contributions for this care from their children. These statistics understate the prevalence of informal and formal care, because only those AHEAD respondents reporting an ADL or IADL problem were asked about the provision of care. Furthermore, in the presence of an ADL or IADL problem, respondents were only asked who provides care if they reported receiving help with the problem "most of the time" and the amount of care is only recorded if the caregiver provided help at least once a week during the month prior to the survey. Thus, our measure does not capture sporadic care.

Moreover, these statistics understate the prevalence of multiple caregivers. In the case of ADLs, the respondent was asked only about the primary caregiver for each reported problem. Thus, respondents reporting a single ADL problem did not have the opportunity to report more than one caregiver. In the case of IADLs, the respondent was asked about the primary and secondary caregiver, if applicable, for a group of reported problems.

Finally, we construct a number of state-specific variables including a price level (BEA, 1999), the cost of home health care[15], and the average home health care state subsidy (HCFA, 1992).

[15] We used wages for home health aide workers in 1993 as reported by the Census of Population and Housing, Earnings by Occupation and Education. These can be found at http://govinfo.kerr.orst.edu/earn-stateis.html.

6 Estimation Strategy

6.1 Empirical Specification

In order to complete the specification of the model, we need to specify the variation of "parameters" across individuals within a family and the joint density of the errors. First, assume that α_{jik} in equation (1) is a function of parent and child characteristics,

$$\alpha_{jik} = \begin{cases} \exp\left\{W_j^0 \delta_\alpha^* + W_k^0 \delta_\alpha^{**}\right\} & \text{if } i = 0 \\ \exp\left\{W_j^0 \delta_\alpha^* + W_{ik} \delta_\alpha^{***}\right\} & \text{if } i > 0 \end{cases} \tag{10}$$

where W_j^0 is a vector of parent-j ($j = m, p$) characteristics, W_k^0 is a vector of characteristics of the spouse (i.e., $k \neq j$), and W_{ik} is a vector of child characteristics for child i ($k = c$) and her spouse ($k = s$). Also, assume that $\log \mu$ is a constant, and the Z_j terms in equation (1) are functions of parent characteristics,

$$Z_j = \exp\left\{W_j^0 \delta_z\right\}. \tag{11}$$

Next, assume that, in equations (2) and (3), $\log \beta_{10}$, $\log \beta_{20}$, and β_{30k} are constant across families (with $\beta_{30k} = 1$), that $\log \beta_{1i}$ ($= \log \beta_{11}$), $\log \beta_{2i}$ ($= \log \beta_{21}$), and $\log \beta_{3ik}$ ($= \log \beta_{31}$) for $i > 0$ are constant across families and children within each family, and that

$$\beta_{4jik} = \begin{cases} W_{jk}^0 \delta_{\beta 4}^* + W_k^0 \delta_{\beta 4}^{**} & \text{if } i = 0 \\ W_{jik} \delta_{\beta 4}^{***} + W_{ik} \delta_{\beta 4}^{****} & \text{if } i > 0 \end{cases} . \tag{12}$$

Note that:

a) β_{30k} and β_{4j0k} cannot be identified separately (except perhaps by functional form) because the parents' leisure time is determined jointly with their caregiving time. Thus, we set $\beta_{30k} = 1$ with no loss in generality.

b) Increasing the constant term in each β term simultaneously has no effect on the first order conditions. Thus, we set $\beta_{2i} = 1$.

For the joint density of the errors, we assume

$$\begin{aligned} \varepsilon_{Xi} &= \exp\{\eta_{Xi}\}, \\ \eta_{Xi} &\sim iidN\left(0, \sigma_{\eta X}^2\right), \\ \varepsilon_{Lik} &= \begin{cases} \exp\{\eta_{Lik}\} \text{ for } i > 0 \\ 1 \text{ for } i = 0 \end{cases}, \\ \begin{pmatrix} \eta_{Lic} \\ \eta_{Lis} \end{pmatrix} &\sim iidN\left(0, \sigma_{\eta L}^2 \begin{pmatrix} 1 & \rho_L \\ \rho_L & 1 \end{pmatrix}\right), \\ \begin{pmatrix} \varepsilon_{tjic} \\ \varepsilon_{tjis} \end{pmatrix} &\sim iidN\left(0, \sigma_{\eta t}^2 \begin{pmatrix} 1 & \rho_t \\ \rho_t & 1 \end{pmatrix}\right), \\ \varepsilon_{tj0k} &\sim iidN\left(0, \sigma_{\eta t}^2\right) \text{ for } j \neq k = m, p, \\ \varepsilon_{ui} &\sim iidN\left(0, \sigma_u^2\right). \end{aligned} \tag{13}$$

As discussed previously, in order to estimate the effects of the explanatory variables, we must restrict the effects of many parameters. In order to determine which parameters to restrict, we considered the results of preliminary data analysis as well as economic intuition. In general, we would restrict a parameter using economic reasoning if it could be argued that, after controlling for the relevant actions, the characteristic would not be expected to influence the health production function or utility function in the manner indicated by the parameter. For example, we would not expect the education of the child to affect how much the child enjoys caring for her parent, after controlling for the amount of care provided; therefore we restrict the child education characteristic corresponding to the parameter $\delta^{****}_{\beta 4}$. In contrast, the number of ADL problems experienced by the parents probably influences the parent's utility associated with caregiving; thus we do not restrict the number of ADLs characteristic corresponding to the parameter $\delta^{*}_{\beta 4}$. We cannot identify the constant terms in δ^{*}_{α} separately from δ^{**}_{α} or δ^{***}_{α}; hence, we restrict the constant terms for δ^{**}_{α} and δ^{***}_{α}.

6.2 The Likelihood Function

The set of parameters to estimate is

$$\begin{aligned} \theta \;=\; & \left(\delta_\alpha, \log\mu, \delta_z, \beta_0, \log\beta_{10},\ \log\beta_{20}, \log\beta_{11}, \log\beta_{21}, \log\beta_{31}, \delta_{\beta 4},\right. \\ & \left.\gamma, \sigma^2_{\eta X}, \sigma^2_{\eta L}, \sigma^2_{\eta t}, \sigma^2_u, \rho_\eta, \rho_t\right), \end{aligned} \tag{14}$$

and the set of data for observation $n = 1, 2, .., N$ is

$$\left\{\left[t_{mik}, t_{pik}, L_{ik}, w_{ik}, W_i, a_{ik}\right]_{k\in c,s}, \widetilde{H_i}, Y_i, p_{Xi}\right\}_{i=1}^{I_n}$$

and

$$\left\{t_{m0p}, t_{p0m}, \widetilde{H_0}, \overline{H}, u_0, Y_0, p_{X0}, q, W^0_m, W^0_p, a_{0p}, a_{0m}\right\}.$$

The variable t_{jik} is time spent caring for parent j by family member ik. Its construction is discussed in Appendix 1. The variable $\widetilde{H_i} = 1$ iff player i paid for care:[16]

$$\widetilde{H_i} = 1\left(H_i > 0\right).$$

The variable $\overline{H}$ is the total amount of paid care:[17]

$$\overline{H} = \sum_{i=0}^{I_n} H_i.$$

The variable

$$L_{ik} = 1 - \sum_{j\in m,p} t_{jik} - PT_{ik}\frac{20}{168} - FT_{ik}\frac{40}{168}$$

[16] The data do not provide enough information to actually determine if $\widetilde{H_0} = 1$. We assume that, if paid care is provided, then some of it is paid for by the parents causing $\widetilde{H_0} = 1$.

[17] It is assumed that both parents, if alive, take advantage of paid care; i.e., that formal care is a public good for the parents' household.

is leisure for family member ik where $PT_{ik} = 1$ iff child i (or child i's spouse) works part-time and $FT_{ik} = 1$ iff child i (or child i's spouse) works full-time. The variable w_{ik} is child i's (or child i's spouse) weekly wage. As discussed earlier, we estimate w_{ik} as a function of the observed characteristics of the child (or spouse) using a different data set. The variable Y_i is a measure of nonlabor income for player i. For the parent, Y_0 is observed. We assume that $Y_i = 0$ for $i > 0$. The variable p_{Xi} is the local price level for player i, and q is the price of care in the parents' state. The variable u_0 is the answer to the question about whether the parent considers herself happy and is treated as a discrete measure of U_0. W_{ik} are exogenous characteristics for child i (or spouse), and W_m^0 and W_p^0 are exogenous parent characteristics. Define

$$\zeta_i = \log\left(\frac{\beta_{1i}\mu p_{Xi} X_i \overline{Q}}{\beta_{2i} q}\right). \tag{15}$$

Also, define

$$\begin{aligned} t_{ji} &= \begin{cases} t_{jik} & \text{if } a_{ik} = 1,\ a_{il} = 0 \text{ for } l = c, s,\ l \neq k \\ (t_{jic}, t_{jis})' & \text{if } a_{ic} = a_{is} = 1 \end{cases}, \\ L_i &= \begin{cases} L_{ik} & \text{if } a_{ik} = 1,\ a_{il} = 0 \text{ for } l = c, s,\ l \neq k \\ (L_{ic}, L_{is})' & \text{if } a_{ic} = a_{is} = 1 \end{cases} \end{aligned}$$

for $i > 0$.

The likelihood contribution for family n, $\pounds_n$, is a product of conditional probabilities over different events (such as whether or not the child contributes time or financial resources to care for the parent). Its structure varies with characteristics of the family's choices and can be written as

$$\begin{aligned} \pounds_n = & \left\{ \Pr\left[u_0 \mid \widetilde{H}_0, t_0\right] \prod_{\substack{j \in m,p \\ k \neq j}} \Pr\left[t_{j0k}\right]^{a_{0k} a_{0j}} \right\} \bullet \\ & \prod_{i:\widetilde{H}_i = 0} \left\{ \int_{\eta_{Xi} \geq \zeta_i} \Pr\left[t_i, L_i \mid \widetilde{H}_i = 0, \varepsilon_{Xi}\right]^{1(i>0)} \frac{1}{\sigma_{\eta X}} \phi\left[\frac{\eta_{Xi}}{\sigma_{\eta X}}\right] d\eta_{Xi} \right\} \bullet \\ & \iiint_{\substack{\eta_{Xi} \leq \zeta_i \\ i:\widetilde{H}_i = 1}} 1\left(\sum_{i:\widetilde{H}_i = 1} H_i(\eta_{Xi}) = \overline{H}\right) \prod_{i:\widetilde{H}_i = 1} \Pr\left[t_i, L_i \mid \widetilde{H}_i = 1\right]^{1(i>0)} \bullet \\ & \frac{1}{\sigma_{\eta X}} \phi\left[\frac{\eta_{Xi}}{\sigma_{\eta X}}\right] d\eta_{Xi} \end{aligned} \tag{16}$$

where

$$H_i(\eta_{Xi}) = \frac{Y_i + w_i\left(1 - L_i - \sum_{j \in m,p} t_{ji}\right) - \frac{\beta_{2i} q}{\beta_{1i}\mu\overline{Q}} \exp\{\eta_{Xi}\}}{q} \tag{17}$$

is derived from equations (8) and the set of first order conditions for the children,

$$\Pr\left[\widetilde{H}_0=0\right] = \Phi\left[\frac{-\log\left(\frac{\beta_{10}\mu p_{X_0}X_0\overline{Q}}{\beta_{20}q}\right)}{\sigma_{\eta X}}\right], \tag{18}$$

$$\Pr\left[u_0 \mid \widetilde{H}_0, t_0\right] = \int\cdots\int \Pr\left[u_0 \mid \eta_{X0}, \eta_{t0}\right] f\left[\eta_{X0}, \eta_{t0} \mid \widetilde{H}_0, t_0\right] d\eta_{X0} d\eta_{t0},$$

$$\Pr\left[u_0 \mid \eta_{X0}, \eta_{t0}\right] = \begin{cases} \Phi\left[\widetilde{U}_0\left(\varepsilon_{X0}, \varepsilon_{t0}\right)\right] & \text{if } u_0=1 \\ 1-\Phi\left[\widetilde{U}_0\left(\varepsilon_{X0}, \varepsilon_{t0}\right)\right] & \text{if } u_0=0 \end{cases},$$

$$\widetilde{U}_0\left(\varepsilon_{X0}, \varepsilon_{t0}\right) = \beta_0+\beta_{10}\sum_{j\in m,p}\ln Q_j+\beta_{20}\varepsilon_{X0}\ln X_0 + \sum_{k\in m,p}\beta_{30k}\ln L_{0k}+\sum_{\substack{j,k\in m,p\\ j\neq k}}\left(\beta_{4j0k+}\varepsilon_{tj0k}\right)t_{j0k},$$

$$\Pr\left[t_{j0k}\right] = \begin{cases} \Phi\left[\frac{T^{t3}_{0jk}(0,\varepsilon_{L0k})}{\sigma_{\eta t}}\right] & \text{if } t_{j0k}=0 \\ \frac{1}{\sigma_{\eta t}}\phi\left[\frac{T^{t3}_{0jk}(t_{j0k},\varepsilon_{L0k})}{\sigma_{\eta t}}\right] & \text{if } t_{j0k}>0 \end{cases},$$

and, for each child i, if $a_{ik}=1$, $a_{il}=0$ for $k,l=c,s;k\neq l$,

$$\Pr\left[t_i, L_i \mid \cdot\right] = \begin{cases} \left|J_n\left(\eta_{Xi}\right)\right|\prod_{j=m,p}P^{t2}_{ijc}\left(\cdot\right)^{a_{0j}}\frac{1}{\sigma_{\eta L}}\phi\left(\frac{\log T^{L2}_{ic}(\varepsilon_{Xi})}{\sigma_{\eta L}}\right) & \text{if } W_{ic}=1 \\ \int_{\log T^{L2}_{ijc}(\varepsilon_{Xi})}^{\infty}\left|J_n\left(\eta_{Xi},\eta_{Lc}\right)\right|\prod_{j=m,p}P^{t3}_{ijc}\left(\cdot\right)^{a_{0j}}\frac{1}{\sigma_{\eta L}}\phi\left(\frac{\eta_{Lc}}{\sigma_{\eta L}}\right)d\eta_{Lc} & \text{if } W_{ic}=0 \end{cases}$$

and, if $a_{ic} = a_{is} = 1$,

$$\Pr\left[t_i, L_i \mid \cdot\right] = \begin{cases} \left|J_n\left(\eta_{Xi}\right)\right| \prod_{j=m,p} R_{ij}^{22t}\left(\cdot\right)^{a_{0j}} B_{12}\left(\frac{\log T_{ijc}^{L2}(\varepsilon_{Xi})}{\sigma_{\eta L}}, \frac{\log T_{ijs}^{L2}(\varepsilon_{Xi})}{\sigma_{\eta L}}, \rho_L\right) \\ \qquad \text{if } H_i = 0,\, W_{ic} = W_{is} = 1 \\ \int_{\log T_{ijs}^{L2}(\varepsilon_{Xi})}^{\infty} \left|J_n\left(\eta_{Xi}, \eta_{Ls}\right)\right| \prod_{j=m,p} R_{ij}^{23t}\left(\cdot\right)^{a_{0j}} \cdot \\ \qquad B_{12}\left(\frac{\log T_{ijc}^{L2}(\varepsilon_{Xi})}{\sigma_{\eta L}}, \frac{\eta_{Ls}}{\sigma_{\eta L}}, \rho_L\right) d\eta_{Ls} \\ \qquad \text{if } H_i = 0,\, W_{ic} = 1,\, W_{is} = 0 \\ \int_{\log T_{ijc}^{L2}(\varepsilon_{Xi})}^{\infty} \left|J_n\left(\eta_{Xi}, \eta_{Lc}\right)\right| \prod_{j=m,p} R_{ij}^{32t}\left(\cdot\right)^{a_{0j}} \cdot \\ \qquad B_{12}\left(\frac{\eta_{Lc}}{\sigma_{\eta L}}, \frac{\log T_{ijs}^{L2}(\varepsilon_{Xi})}{\sigma_{\eta L}}, \rho_L\right) d\eta_{Lc} \\ \qquad \text{if } H_i = 0,\, W_{ic} = 0,\, W_{is} = 1 \\ \left|J_n\left(\eta_{Xi}\right)\right| \prod_{j=m,p} R_{ij}^{22t}\left(\cdot\right)^{a_{0j}} B_{12}\left(\frac{\log T_{ijc}^{L1}}{\sigma_{\eta L}}, \frac{\log T_{ijs}^{L1}}{\sigma_{\eta L}}, \rho_L\right) \\ \qquad \text{if } H_i = 1,\, W_{ic} = W_{is} = 1 \\ \int_{\log T_{ijs}^{L2}(\varepsilon_{Xi})}^{\infty} \left|J_n\left(\eta_{Xi}, \eta_{Ls}\right)\right| \prod_{j=m,p} R_{ij}^{23t}\left(\cdot\right)^{a_{0j}} \cdot \\ \qquad B_{12}\left(\frac{\log T_{ijc}^{L1}}{\sigma_{\eta L}}, \frac{\eta_{Ls}}{\sigma_{\eta L}}, \rho_L\right) d\eta_{Ls} \\ \qquad \text{if } H_i = 1,\, W_{ic} = 1,\, W_{is} = 0 \\ \int_{\log T_{ijc}^{L2}(\varepsilon_{Xi})}^{\infty} \left|J_n\left(\eta_{Xi}, \eta_{Lc}\right)\right| \prod_{j=m,p} R_{ij}^{32t}\left(\cdot\right)^{a_{0j}} \cdot \\ \qquad B_{12}\left(\frac{\eta_{Lc}}{\sigma_{\eta L}}, \frac{\log T_{ijs}^{L1}}{\sigma_{\eta L}}, \rho_L\right) d\eta_{Lc} \\ \qquad \text{if } H_i = 1,\, W_{ic} = 0,\, W_{is} = 1 \\ \int_{\log T_{ijc}^{L2}(\varepsilon_{Xi})}^{\infty} \int_{\log T_{ijs}^{L2}(\varepsilon_{Xi})}^{\infty} \left|J_n\left(\eta_{Xi}, \eta_{Lc}, \eta_{Ls}\right)\right| \prod_{j=m,p} R_{ij}^{33t}\left(\cdot\right)^{a_{0j}} \cdot \\ \qquad B_{12}\left(\frac{\eta_{Lc}}{\sigma_{\eta L}}, \frac{\eta_{Lc}}{\sigma_{\eta L}}, \rho_L\right) d\eta_{Ls} d\eta_{Lc} \\ \qquad \text{if } W_{ic} = W_{is} = 0 \end{cases}$$

$$\begin{aligned} P_{ijc}^{t2}\left(\cdot\right) &= \begin{cases} \Phi\left(\frac{T_{ijc}^{t2}(0,\varepsilon_{Xi})}{\sigma_{\eta t}}\right) & \text{if } t_{jic} = 0,\, H_i = 0 \\ \frac{1}{\sigma_{\eta t}}\phi\left(\frac{T_{ijc}^{t2}(t_{jic},\varepsilon_{Xi})}{\sigma_{\eta t}}\right) & \text{if } t_{jic} > 0,\, H_i = 0 \\ \Phi\left(\frac{T_{ijc}^{t1}(0)}{\sigma_{\eta t}}\right) & \text{if } t_{jic} = 0,\, H_i = 1 \\ \frac{1}{\sigma_{\eta t}}\phi\left(\frac{T_{ijc}^{t1}(t_{jic})}{\sigma_{\eta t}}\right) & \text{if } t_{jic} > 0,\, H_i = 1 \end{cases} \\ P_{ijc}^{t3}\left(\cdot\right) &= \begin{cases} \Phi\left(\frac{T_{ijc}^{t3}(0,\varepsilon_{Lic})}{\sigma_{\eta t}}\right) & \text{if } t_{jic} = 0 \\ \frac{1}{\sigma_{\eta t}}\phi\left(\frac{T_{ijc}^{t3}(t_{jic},\varepsilon_{Lic})}{\sigma_{\eta t}}\right) & \text{if } t_{jic} > 0 \end{cases} \end{aligned}$$

$$
R_{ij}^{22t}\left(\cdot\right)=\begin{cases}
B\left(\frac{T_{ijc}^{t2}(0,\varepsilon_{Xi})}{\sigma_{\eta t}},\frac{T_{ijs}^{t2}(0,\varepsilon_{Xi})}{\sigma_{\eta t}},\rho_t\right) & \text{if } t_{jic}=t_{jis}=0,\, H_i=0\\
B_1\left(\frac{T_{ijc}^{t2}(t_{jic},\varepsilon_{Xi})}{\sigma_{\eta t}},\frac{T_{ijs}^{t2}(0,\varepsilon_{Xi})}{\sigma_{\eta t}},\rho_t\right) & \text{if } t_{jic}>0,\, t_{jis}=0,\, H_i=0\\
B_2\left(\frac{T_{ijc}^{t2}(0,\varepsilon_{Xi})}{\sigma_{\eta t}},\frac{T_{ijs}^{t2}(t_{jis},\varepsilon_{Xi})}{\sigma_{\eta t}},\rho_t\right) & \text{if } t_{jic}=0,\, t_{jis}>0,\, H_i=0\\
B_{12}\left(\frac{T_{ijc}^{t2}(t_{jic},\varepsilon_{Xi})}{\sigma_{\eta t}},\frac{T_{ijs}^{t2}(t_{jis},\varepsilon_{Xi})}{\sigma_{\eta t}},\rho_t\right) & \text{if } t_{jic}>0,\, t_{jis}>0,\, H_i=0\\
B\left(\frac{T_{ijc}^{t1}(0)}{\sigma_{\eta t}},\frac{T_{ijs}^{t1}(0)}{\sigma_{\eta t}},\rho_t\right) & \text{if } t_{jic}=t_{jis}=0,\, H_i=1\\
B_1\left(\frac{T_{ijc}^{t1}(t_{jic})}{\sigma_{\eta t}},\frac{T_{ijs}^{t1}(0)}{\sigma_{\eta t}},\rho_t\right) & \text{if } t_{jic}>0,\, t_{jis}=0,\, H_i=1\\
B_2\left(\frac{T_{ijc}^{t1}(0)}{\sigma_{\eta t}},\frac{T_{ijs}^{t1}(t_{jis})}{\sigma_{\eta t}},\rho_t\right) & \text{if } t_{jic}=0,\, t_{jis}>0,\, H_i=1\\
B_{12}\left(\frac{T_{ijc}^{t1}(t_{jic})}{\sigma_{\eta t}},\frac{T_{ijs}^{t1}(t_{jis})}{\sigma_{\eta t}},\rho_t\right) & \text{if } t_{jic}>0,\, t_{jis}>0,\, H_i=1
\end{cases}
$$

$$
R_{ij}^{23t}\left(\cdot\right)=\begin{cases}
B\left(\frac{T_{ijc}^{t2}(0,\varepsilon_{Xi})}{\sigma_{\eta t}},\frac{T_{ijs}^{t3}(0,\varepsilon_{Lis})}{\sigma_{\eta t}},\rho_t\right) & \text{if } t_{jic}=t_{jis}=0,\, H_i=0\\
B_1\left(\frac{T_{ijc}^{t2}(t_{jic},\varepsilon_{Xi})}{\sigma_{\eta t}},\frac{T_{ijs}^{t3}(0,\varepsilon_{Lis})}{\sigma_{\eta t}},\rho_t\right) & \text{if } t_{jic}>0,\, t_{jis}=0,\, H_i=0\\
B_2\left(\frac{T_{ijc}^{t2}(0,\varepsilon_{Xi})}{\sigma_{\eta t}},\frac{T_{ijs}^{t3}(t_{jis},\varepsilon_{Lis})}{\sigma_{\eta t}},\rho_t\right) & \text{if } t_{jic}=0,\, t_{jis}>0,\, H_i=0\\
B_{12}\left(\frac{T_{ijc}^{t2}(t_{jic},\varepsilon_{Xi})}{\sigma_{\eta t}},\frac{T_{ijs}^{t3}(t_{jis},\varepsilon_{Lis})}{\sigma_{\eta t}},\rho_t\right) & \text{if } t_{jic}>0,\, t_{jis}>0,\, H_i=0\\
B\left(\frac{T_{ijc}^{t1}(0)}{\sigma_{\eta t}},\frac{T_{ijs}^{t3}(0,\varepsilon_{Lis})}{\sigma_{\eta t}},\rho_t\right) & \text{if } t_{jic}=t_{jis}=0,\, H_i=1\\
B_1\left(\frac{T_{ijc}^{t1}(t_{jic})}{\sigma_{\eta t}},\frac{T_{ijs}^{t3}(0,\varepsilon_{Lis})}{\sigma_{\eta t}},\rho_t\right) & \text{if } t_{jic}>0,\, t_{jis}=0,\, H_i=1\\
B_2\left(\frac{T_{ijc}^{t1}(0)}{\sigma_{\eta t}},\frac{T_{ijs}^{t3}(t_{jis},\varepsilon_{Lis})}{\sigma_{\eta t}},\rho_t\right) & \text{if } t_{jic}=0,\, t_{jis}>0,\, H_i=1\\
B_{12}\left(\frac{T_{ijc}^{t1}(t_{jic})}{\sigma_{\eta t}},\frac{T_{ijs}^{t3}(t_{jis},\varepsilon_{Lis})}{\sigma_{\eta t}},\rho_t\right) & \text{if } t_{jic}>0,\, t_{jis}>0,\, H_i=1
\end{cases}
$$

$$
R_{ij}^{32t}\left(\cdot\right)=\begin{cases}
B\left(\frac{T_{ijc}^{t3}(0,\varepsilon_{Lic})}{\sigma_{\eta t}},\frac{T_{ijs}^{t2}(0,\varepsilon_{Xi})}{\sigma_{\eta t}},\rho_t\right) & \text{if } t_{jic}=t_{jis}=0,\, H_i=0\\
B_1\left(\frac{T_{ijc}^{t3}(t_{jic},\varepsilon_{Lic})}{\sigma_{\eta t}},\frac{T_{ijs}^{t2}(0,\varepsilon_{Xi})}{\sigma_{\eta t}},\rho_t\right) & \text{if } t_{jic}>0,\, t_{jis}=0,\, H_i=0\\
B_2\left(\frac{T_{ijc}^{t3}(0,\varepsilon_{Lic})}{\sigma_{\eta t}},\frac{T_{ijs}^{t2}(t_{jis},\varepsilon_{Xi})}{\sigma_{\eta t}},\rho_t\right) & \text{if } t_{jic}=0,\, t_{jis}>0,\, H_i=0\\
B_{12}\left(\frac{T_{ijc}^{t3}(t_{jic},\varepsilon_{Lic})}{\sigma_{\eta t}},\frac{T_{ijs}^{t2}(t_{jis},\varepsilon_{Xi})}{\sigma_{\eta t}},\rho_t\right) & \text{if } t_{jic}>0,\, t_{jis}>0,\, H_i=0\\
B\left(\frac{T_{ijc}^{t3}(0,\varepsilon_{Lic})}{\sigma_{\eta t}},\frac{T_{ijs}^{t1}(0)}{\sigma_{\eta t}},\rho_t\right) & \text{if } t_{jic}=t_{jis}=0,\, H_i=1\\
B_1\left(\frac{T_{ijc}^{t3}(t_{jic},\varepsilon_{Lic})}{\sigma_{\eta t}},\frac{T_{ijs}^{t1}(0)}{\sigma_{\eta t}},\rho_t\right) & \text{if } t_{jic}>0,\, t_{jis}=0,\, H_i=1\\
B_2\left(\frac{T_{ijc}^{t3}(0,\varepsilon_{Lic})}{\sigma_{\eta t}},\frac{T_{ijs}^{t1}(t_{jis})}{\sigma_{\eta t}},\rho_t\right) & \text{if } t_{jic}=0,\, t_{jis}>0,\, H_i=1\\
B_{12}\left(\frac{T_{ijc}^{t3}(t_{jic},\varepsilon_{Lic})}{\sigma_{\eta t}},\frac{T_{ijs}^{t1}(t_{jis})}{\sigma_{\eta t}},\rho_t\right) & \text{if } t_{jic}>0,\, t_{jis}>0,\, H_i=1
\end{cases}
$$

$$
R_{ij}^{33t}\left(\cdot\right)=\begin{cases}
B\left(\frac{T_{ijc}^{t3}(0,\varepsilon_{Lic})}{\sigma_{\eta t}},\frac{T_{ijs}^{t3}(0,\varepsilon_{Lis})}{\sigma_{\eta t}},\rho_t\right) & \text{if } t_{jic}=t_{jis}=0\\
B_1\left(\frac{T_{ijc}^{t3}(t_{mic},\varepsilon_{Lic})}{\sigma_{\eta t}},\frac{T_{ijs}^{t3}(0,\varepsilon_{Lis})}{\sigma_{\eta t}},\rho_t\right) & \text{if } t_{jic}>0,\, t_{jis}=0\\
B_2\left(\frac{T_{ijc}^{tc}(0,\varepsilon_{Lic})}{\sigma_{\eta t}},\frac{T_{ijs}^{t3}(t_{jis},\varepsilon_{Lis})}{\sigma_{\eta t}},\rho_t\right) & \text{if } t_{jic}=0,\, t_{jis}>0\\
B_{12}\left(\frac{T_{ijc}^{t3}(t_{jic},\varepsilon_{Lic})}{\sigma_{\eta t}},\frac{T_{ijs}^{t3}(t_{jis},\varepsilon_{Lis})}{\sigma_{\eta t}},\rho_t\right) & \text{if } t_{jic}>0,\, t_{jis}>0
\end{cases},
$$

$B\left(\frac{x_1}{\sigma}, \frac{x}{\sigma}, \rho\right)$ is the standard bivariate normal distribution function with mean 0 and covariance matrix

$$\sigma^2 \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix},$$

where

$$\begin{aligned} B_j\left(\frac{x_1}{\sigma}, \frac{x_2}{\sigma}, \rho\right) &= \frac{\partial}{\partial x_j} B\left(\frac{x_1}{\sigma}, \frac{x_2}{\sigma}, \rho\right) \\ B_{jk}\left(\frac{x_1}{\sigma}, \frac{x_2}{\sigma}, \rho\right) &= \frac{\partial^2}{\partial x_j \partial x_k} B\left(\frac{x_1}{\sigma}, \frac{x_2}{\sigma}, \rho\right). \end{aligned}$$

and J_n is the Jacobian corresponding to those errors with interior solutions.

Some of the terms in the likelihood function need to be simulated. While simulation of most terms is straightforward, simulation of the last term is more complicated. We discuss how to do this using a GHK algorithm (Hajivassiliou, McFadden, and Ruud, 1996) in Appendix 2.

6.3 Identification

The set of parameters to estimate is listed in equation (14). Asymptotically, we can observe consistently the covariation of each dependent variable with the set of exogenous variables. It is this covariation that allows us to identify all of the structural parameters.[18] The effect of parent exogenous variables on baseline health Z, measured by δ_z in equation (11), is identified by covariation between parent characteristics and the "happy variable," u_0. The effects of exogenous variables on parent and child utility, measured by $\delta_{\beta 4}$ in equation (12) and $\log \beta_{10}$, $\log \beta_{20}$, $\log \beta_{11}$, $\log \beta_{21}$, and $\log \beta_{31}$, are identified by covariation between parent and child characteristics and parent and child choices. For example, the degree that the parent's problems with ADLs move with child informal care t identifies the effect of parent ADLs on β_4. Note that covariation between parent characteristics and children's care decisions does not identify δ_z because parent characteristics can directly affect care decisions through $\delta_{\beta 4}$. The effect of parent and child characteristics on the quality of care, measured by δ_α in equation (10), is identified by the covariation between $\partial \Pr\left[u_0 = 1 \mid t\right] / \partial t$ and parent and child characteristics. For example, because the partial correlation between parent happiness and informal care provision decreases with the distance between the parent and the child caregiver, the δ_α coefficient on distance is negative. Thus, we should observe that the observed slope of $\Pr\left[u_0 = 1 \mid t\right]$ with respect to t varies with distance appropriately. The term γ in equation (1) is identified by $\partial^2 \Pr\left[u_0 = 1 \mid t\right] / \partial t^2$. The effectiveness of formal care, measured by $\log \mu$, is identified by the covariation between u_0 and the provision of formal care, $\overline{H}$. The term β_0 in equations (2) and (3) is not of interest by

[18] Of course, there is the possibility of singularity not considered in this discussion. The final argument for identification is empirical: the Hessian of the log likelihood function is non-singular.

itself. But it is needed to match the mean of the "happy variable" data and is identified by the mean. Second moment terms, $\sigma^2_{\eta X}$, $\sigma^2_{\eta L}$, $\sigma^2_{\eta t}$, σ^2_u, ρ_η, and ρ_t, are identified by variances and correlations of generalized residuals (Gourieroux et al. 1987) associated with the likelihood function.

Note that the provision of informal care t affects a family member's utility in two ways: it directly affects utility through the satisfaction (or sense of burden) one receives (the β_4 effect), and it improves the parent's health thus affecting the child's utility (the β_1 effect). In much of the literature on informal care, the theory does not really specify which mechanism is relevant. In almost all of the literature, there is no attempt to identify the two effects separately. Hiedemann and Stern (1999) argue that all children derive utility from the health benefits of informal care but only the caregiver derives satisfaction or burden from it. Thus, Hiedemann and Stern identify the separate effects by variation in care provision across families of different sizes. We are making the same assumption, but the effect of informal care on identification is completely different because the games being played in the two models are very different. In this work, the inclusion of the "happy variable" allows us to directly measure the effect of formal and informal care on the parent's well-being, and that allows us to disentangle the two effects. For example, if we were to observe that the provision of informal care by children has a very small empirical effect on the parent's happiness relative to the effect of variables affecting Z, we would conclude that α is very small and $\beta_4 > 0$. Alternatively, if we were to observe that very little informal care is provided but those parents who receive it are usually happier, we would conclude that α is large and $\beta_4 < 0$. Note that the inclusion of the "happy data" allows us to nonparametrically identify all of the parameters because terms like $\partial \Pr[u_0 = 1 \mid t] / \partial t$ and its covariation with observed variables are nonparametrically identified. The model structure tells us how to decompose $\partial \Pr[u_0 = 1 \mid t] / \partial t$ into $\partial \Pr[u_0 = 1 \mid t] / \partial Q$ and $\partial Q / \partial t$, but the model works regardless of the decomposition.

7 Results

7.1 Model Without Covariates

We estimated several variants of our model. The results of a preliminary model with no covariates are displayed in Table 6. The relevant unit is a util as measured by the standard deviation of ε_{ui} in equation (3). A fruitful approach to interpreting estimates involves comparing derivatives of utility with respect to two different choice variables. For example, the cost to a child of spending an extra hour caring for a parent relative to taking the time as leisure is $\left(\beta_{4jik} + \varepsilon_{tjik}\right) / \left[\beta_{3ik} \varepsilon_{Lik} \frac{\partial \ln L_{ik}}{\partial L_{ik}}\right]$.

The estimates suggest that both formal and informal care have little effect on the parent's health and that there are diseconomies of scale associated with informal care. The effects of an additional hour of formal care and informal care provided by a particular family member on the parent's health are μ and

$\alpha(1+2\gamma t)$, respectively. Although $\log \mu$ is significantly less than 0, the estimated effect of formal care on the parent's health is very small. An additional hour of informal care provided by a particular family member enhances the parent's health for levels of care of 8.1 hours per week or less. Beyond that point, additional informal care provided by the family member in question actually diminishes the parent's health. Note, however, that $\log \alpha$ is not significantly different from 0. The results suggest that, while not very productive in terms of enhancing the parent's health, informal care is burdensome: β_{40} and β_{4i} are significantly less than 0. Moreover, the burden associated with caregiving is large relative to the estimated effects of informal care on the parent's health α (ignoring γ effects) and the effect of the parent's health on her utility β_{10}. These relative magnitudes may explain why few children and spouses provide care for elderly individuals.

The estimates of $\sigma_{\eta X}$ and $\sigma_{\eta L}$ relative to $\beta_2 (\equiv 1)$ and β_3 suggest that there is significant variation in the marginal value of consumption and leisure across families. For example, while the mean marginal utility with respect to log consumption is 1, 10% have marginal utility above 4.16 and 10% have marginal utility below 0.24.[19] Similarly, for leisure, the average marginal utility is 1.40, but 10% have marginal utility above 6.98, while 10% have marginal utility below 0.28.

The estimate of $\sigma_{\eta t}$ suggests that 9.9% of elderly spouses and 3.5% of adult children enjoy spending time caring for the elderly individual ($\beta_4 + \varepsilon_t > 0$). The estimates of ρ_L and ρ_t suggest that child/spouse-specific marginal values of leisure and caregiving are very highly positively correlated. Thus, the results suggest that the child and his or her spouse tend to view their time as strong complements.

7.2 Model With Covariates

We estimated a model with covariates that allows the α and Z terms in equation (1) and the β_4 in equations (2) and (3) to depend on covariates. This model allows family members' characteristics to affect both the quality of care provided and the burden associated with caregiving. The results are presented in Table 7.

Parents care about their health in that it affects their utility ($\log \beta_1 = -0.722$). Checkovitch and Stern (2002) and Pezzin and Schone (1999) provide evidence that children provide more informal care as the parent ages. Similarly, our results suggest that children receive insignificantly more utility from caregiving as the parent ages. However, care provided by a child becomes significantly less productive as a parent ages. Thus, children may provide less informal care as the parent ages. These two effects are identified from one another because both effects influence the amount of time children spend providing care, but only the latter effect influences the parent's utility.

[19] $\widehat{\sigma}_{\eta X} = 1.114$, so the 80% confidence interval for $\eta_X = \pm 1.426$. This implies the reported 80% confidence interval for $\beta_2 \varepsilon_x$.

As the parent accumulates ADL problems, caregiving becomes less effective and more burdensome. These results imply that, as a parent accumulates ADL problems, she will recieve less care from her children. In contrast, Checkovitch and Stern (2002) and Sloan, Picone, and Hoerger (1997) report evidence that children provide more informal care as the parent develops more problems with ADLs.

Previous studies provide mixed evidence on the relationship between the parent's gender and informal care provision by children. Hiedemann and Stern (1999) report that family members value care provided for mothers more than care provided for fathers, while Pezzin and Schone (1999) indicate that daughters are more likely to provide care for fathers than for mothers. We find that informal care is significantly more effective and insignificantly less burdensome for mothers than for fathers. Not surprisingly in light of the mixed evidence reported by other studies (Stern 1995, Wolf 1984, and Spear and Avery 1993), race does not significantly influence the effectiveness or the burden associated with caregiving. As expected, the parent's health declines with age and ADL problems. Married parents are healthier than their single counterparts.

As expected, care provided by the spouse becomes less effective as the spouse accumulates ADL problems. But, counter to expectations, care provided by the spouse become more effective as the spouse ages. Care provided by children becomes less effective as the child ages, but older children receive more utility from caregiving.

The existing literature provides evidence on the relationship between a child's gender and the provision of care for elderly parents. Engers and Stern (2002), Checkovitch and Stern (2002), and Sloan, Picone, and Hoerger (1997) find that, all else equal, daughters are significantly more likely than sons to provide care. Interestingly, however, Sloan, Picone, and Hoerger's findings indicate that sons provide significantly more care than daughters. This result holds regardless of whether they control for selection into the primary caregiving role. Hiedemann and Stern's (1999) results suggest that family members value care provided by daughters more than care provided by sons. The results presented in this paper suggest that sons are slightly and statistically insignificantly less effective as caregivers than are daughters ($0.389 - 0.449 = -0.06$). In addition, sons receive less utility caring for parents than do daughters ($-1.262 + 0.851 = -0.411$) but again by a statistically insignificant amount. Recall that, on average, sons earn more than daughters, and we control for differences in opportunity costs. Thus, the results suggest that gender differences in the provision of care for elderly parents are partially due to variation in opportunity costs and partially due to variation in care effectiveness and preferences.

Sons provide lower quality care than sons-in-law ($0.110 - 0.449 = -0.339$),[20] and daughters provide statistically insignificantly better care than do daughters-in-law (0.110). Sons receive more utility from providing care than do sons-in-law ($-0.376 + 0.851 = 0.475$), but daughters-in-law receive more utility from

[20] Perhaps, sons-in-law provide better care than sons because they are the husbands of daughters.

providing care than do daughters (-0.376) but both effects are statistically insignificant.

Sloan, Picone, and Hoerger (1997) report that married children provide less care for elderly parents. Similarly, Pezzin and Schone (1999) report that the probability that a daughter who lives separately from her parents provides informal care depends negatively on the number of her own children. Our results indicate that married children provide higher quality care but experience greater burden providing care. Similarly, the quality of care and the burden associated with caregiving depend positively on the number of one's own children. These results suggest that caring for elderly parents is particularly burdensome for adult children with family responsibilities. The results reveal diminishing marginal productivity of time spent caring for elderly parents ($\gamma < 0$). Informal care becomes counterproductive ($\partial Q/\partial t \leq 0$) at $t = 0.0855$ (14.4 hours per week).

Given the unobserved and observed variation in α, β, Z, and utility across family members and across families, interpreting some of the coefficients is difficult. Table 8 provides the first two moments of these parameters across the population. Informal care appears to be somewhat ineffective (the average $\log \alpha$ is a large negative number), particularly when provided by children or children-in-law rather than by the spouse. Parents and children care about the health of the parent, suggesting that altruism is an important motivation for family decision making. Finally caregiving is almost always burdensome: β_4 is almost always negative.

Table 9 illustrates the implications of the magnitude of $\log \alpha$ by way of two "representative individuals" described in the notes to the table. For both individuals, increasing informal care from zero to 20 hours per week ($t = 0.12$) mitigates a small but nontrivial part of the effect on well being (Q) of accumulating an ADL problem. For example, for individuals 1 and 2, 20 hours of informal care increases Q by 2.3% and 18.9% respectively, while the first ADL problem decreases Z, and therefore Q, by 28.7%. One might wonder how much of an increase in caregiving by a child would be necessary to offset the effect of an extra ADL on Q. In fact, one child cannot counterbalance the effect of an extra ADL. For example, for the first representative individual in Table 9, an extra ADL decreases Z/α by 0.69; this would have to be the increase in $t + \gamma t^2$. But, given the large, negative value of γ, $\max_t \left(t + \gamma t^2\right) = 0.043$.

7.3 Decompositions

To shed light on gender differences in the provision of informal care, we first examine the roles of opportunity costs, effectiveness in the caregiving role, and burden associated with caregiving in adult children's likelihood of providing informal care. Table 10 decomposes these effects by the child's marital status and the number of children. For all family sizes, the benchmark is an unmarried daughter. For example, consider families that consist of only one adult child who is not married. As indicated in the first column, the overall probability that the child provides care is 0.033 for daughters and 0.011 for sons. Each of the next three columns allows for one of the three types of effects: 1) opportunity costs as measured by wages, 2) effectiveness as a caregiver (quality of care), or 3) burden. For example, allowing for gender differences in wages but not in quality or burden, the probability that a son provides care is 0.030. Allowing for gender differences in quality only, the probability that a son provides care is 0.041. Allowing for gender differences in burden only, this probability falls to 0.009. As indicated in the last column, in the absence of wage, quality, or burden effects, the gender gap virtually disappears for only children: the probability that an only child provides care is 0.033 for daughters and 0.032 for sons. Thus there are no other important characteristics varying with child gender that affect care.

In the case of married daughters, the table provides the probability that daughters and/or their husbands provide informal care; similarly, for married sons, the table provides the probability that sons and/or their wives provide care.

Table 10 reports the probability that an adult child provides informal care conditional on gender, marital status, and family size and isolates the effects of opportunity costs, caregiving effectiveness, and caregiving burden on these probabilities. But the more interesting question concerns the extent to which opportunity costs, quality, and burden contribute to gender differences in the propensity to provide informal care. Table 11 reports cross partial differences of log probabilities with respect to the effect in question and gender. Consider families that consist of only one adult child who is not married. Table 11 indicates that opportunity costs reduce the probability that a son provides informal care by 7%, quality of care effects increase the probability by 28%, and the burden associated with caregiving reduces the probability by 73% relative to the same effects for a daughter. As shown in Table 7, sons feel more burden caring for parents than do daughters ($\frac{\Delta\beta_4}{\Delta Male} = -1.262 + .851 = -0.411$), so

$$\frac{\Delta^2 \log \Pr[t > 0]}{\Delta\beta_4 \Delta Male} \approx \frac{\partial \log \Pr[t > 0]}{\partial \beta_4} \frac{\Delta\beta_4}{\Delta Male} \approx -1.3.$$

Allowing for all effects reduces the probability that a son provides care by 66% relative to a daughter.

Now consider families that consist of only one adult child who is married. The effects change because each household consists of one adult male and one adult female. Overall sons and/or their wives are 15% less likely to provide care than are daughters and/or their husbands. Allowing for gender differences in quality but not in burden or wages, sons and/or their wives are 30% less likely to provide care as daughters and/or their husbands. Allowing for gender differences in burden only, sons and/or their wives are 19% more likely to provide care than are daughters and/or their husbands. Allowing for gender differences in wages only, there is virtually no difference in the probability that sons and/or their wives or daughters and/or their husbands provide care. The results are fairly robust to changes in family size.

We also performed a similar exercise for race. Table 12 shows the effects of changing various characteristics of blacks to make them similar to whites. On average, blacks spend more time caregiving than do whites. Although differences in opportunity costs by race contribute to differences in caregiving time, burden plays a larger role. Blacks experience less burden from caregiving. Black parents receive smaller benefit from informal care than do white parents, somewhat offsetting the effects of opportunity cost and burden.[21]

7.4 Specification Tests

We performed two types of specification tests. First, we tested for the existence of state fixed effects. We aggregated residuals for 34 states with at least 4 observations. We could not reject the null hypothesis of no state fixed effects for time spent caring for the parent, financial contributions, and leisure.

Next we performed a set of χ^2 goodness-of-fit tests for informal care, financial contributions towards formal care, and leisure. For each variable x (time spent helping per family member, proportion of family members offering financial help, and leisure per family member), we simulated x twenty times for each family n and computed the mean $\widehat{x}$ and the standard deviation $\widehat{s}$. Then we constructed

$$\chi_{1n}^2 = \frac{(x_n - \widehat{x})^2}{\widehat{s}^2 + \sigma_m^2} \tag{19}$$

where σ_m^2 is a correction for measurement error. Its construction is discussed in Appendix 3. We then summed χ_{1n}^2 over n. The results of this exercise are presented in Table 13, disaggregated by family size. The χ^2 statistics are all very large, but, with the exception of financial help in small families, the mean residuals are quite small. For example, the mean residual on "time help" for families of size 4 means that we overestimate time help in such families by 1% on average.

The large χ^2 statistics are caused by outliers to a great degree. In fact, if we censor each χ_{1n}^2 statistic in equation (19) at the 1% level, i.e.,

$$\chi_{1n}^{2*} = \min\left[\frac{(x_n - \widehat{x})^2}{\widehat{s}^2 + \sigma_m^2}, 6.63\right],$$

then the χ^2 statistics reduce to the numbers in the column labeled "Censored." The next column shows the number of χ_{1n}^{2*} statistics that are actually censored, and the last column turns the censored χ^2 statistic into a standard normal random variable. The results suggest that we are still missing some aspect of decision making with respect to informal care though not in terms of average caregiving time. On the other hand, after controlling for a small number of outliers, we are predicting financial help and leisure decisions quite accurately.

7.5 Policy Experiments

We consider the effects of six experiments on family behavior given the parameter estimates reported in Table 7. The six experiments involve:

[21] It should be noted that the burden and quality effects are not statistically significant.

1. providing a subsidy of qF to each parent that must be used for formal care (formal care stamps);
2. providing a subsidy of F to each child or child-in-law for each unit of time she provides informal care;
3. providing a subsidy of F for each dollar spent on formal care (reduction in the price of formal care);
4. providing a lump sum of F to the parent;
5. increasing Ψ, the income limit for Medicaid; and
6. providing a subsidy of qF to each parent for each ADL problem; this subsidy must be used for formal care.

Appendix 4 provides the details of how to evaluate the effects of each of these policy experiments. Given the small marginal product of formal and informal care on Q implied by the parameter estimates in Table 7, almost all of the policy experiments would have essentially no effect on behavior. Experiment (1) suggests that formal care stamps would increase expenditures by about \$0.35 for every dollar spent on the program for families with children. Most families without formal care expenditures prior to the experiment would exhaust their formal care stamps but spend no out of pocket funds on formal care. To a significant degree, those with formal care expenditures would replace their own expenditures with program expenditures with little effect on the level of formal care.

Experiments (2) and (3) essentially reduce the price of informal and formal care. In the average family with two children, a \$1.00 subsidy per hour would result in an increase of 2.1 hours per week of caregiving by children (with a corresponding small reduction of hours per week of caregiving by parents). However, since the family resources expended on both are small and both marginal products are small, the effects of the subsidy would be small. Experiment (3) would have only trivial effects because formal care expenditures are very small. Experiment (4) indicates that a lump sum subsidy to the parent would be used to supplement consumption. Thus, a lump sum subsidy would have very little effect on formal or informal care or the health (Q) of the parent. Experiments (5) and (6) are small deviations of experiment (1) and would have similar though smaller effects.

Overall, the results of these experiments suggest that variation in state Medicaid policy would have little effect on long-term care decisions. These results are consistent with results in Engers and Stern (2002) where no significant state effects were found but inconsistent with Cutler and Sheiner (1993) that found small macro effects. We measure the effect of policy changes given respondents reside in the community and hence, under some situations, underestimate the effect of changes in policy on community-based care giving. For example, policy changes with regard to Medicaid income limits or subsidies for home health care may imply different choices for community-based care versus institutionalization. Institutional care may be a decision under some policy parameters, while other policy parameters may induce families to care for the elderly parent at home.

8 Conclusions

We develop and estimate a game-theoretic model of families' decisions concerning the provision of formal and informal care for elderly individuals. Our game-theoretic framework allows preferences over consumption, leisure, and the health status of the elderly individual(s) to vary across family members. In our model, each individual or married couple makes caregiving decisions conditional on the decisions of the other family members. We use the first-order conditions of the model to solve for the errors as relatively simple functions of the parameters and construct a likelihood function for estimation.

The structure of the model allows us to distinguish among three underlying explanations for patterns in care provision. First, some family members find providing care more burdensome than do others. Second, some members are more adept at providing care. Third, opportunity costs in the form of foregone earnings vary across the family. We find that caring for an elderly parent or spouse is burdensome for most individuals and that informal care has a relatively small effect on health quality. Consequently, children and spouses provide little informal care. We use the structure to shed light on why, in the raw data, daughters are more likely than sons to provide care and why blacks are more likely than whites to provide care. Differences in burden and quality of care dominate opportunity costs, but the effects vary by marital status of the children.

Goodness of fit tests show that our model fits the data fairly well. In addition, we fail to reject the hypothesis that there is no additional variation across states not captured in our model. This result suggests that our simplification of the Medicaid benefit structure performs well.

We exploit the structural nature of the estimates to perform policy experiments similar to those suggested in public policy discussions. For example, we simulate the provision of a lump sum that can be spent only on care as well as price subsidies for informal and formal home care. Consistent with the finding that formal and informal home care are largely ineffective in increasing health quality, we find little effect of these policy changes.

These results should be interpreted carefully in light of the nature of our data. The first wave of AHEAD data does not include any nursing home residents. Subsequent waves of AHEAD contain nursing home residents and will thus allow us to include them in the model. The survey instrument was also improved in later waves to elicit information about more caregivers.

In addition, the availability of panel data will enable us to estimate dynamic models of care arrangements for elderly individuals. In particular, we plan to estimate a dynamic extension of our structural model with more waves of AHEAD data. Using panel data, we can explore whether siblings take turns caregiving or whether certain children specialize in caregiving while others specialize in market production or other forms of nonmarket production. If children do, in fact, take turns caregiving, the use of panel data will enable us to examine possible causes of this behavior including burnout.

Moreover, the inclusion of nursing home residents in subsequent waves of AHEAD provides us with an opportunity to investigate the effects of proposed or actual policies on the use of institutional care. For example, subsidies for home health care may induce some families to care for the elderly at home rather than in an institution.

9 Appendix 1: Construction of Child Caring Time

A key issue in estimation concerns the interpretation of data on caregiving time t_{jik}. In the survey, there are two relevant questions:

1) How many days per week does the helper provide help?; and

2) How many hours per day does the helper provide help on days when she helps?

While the responses to the second question provide a continuous measure of hours per day, responses to the first question are categorical: a) every day, b) several times a week, c) once per week, d) less than once per week, and e) never. We can use the answers to these two questions to construct a "pseudo" continuous variable:

$$t_{jik} = \begin{cases} 7\pi_{jik}/168 & \text{if she helps every day} \\ 3.5\pi_{jik}/168 & \text{if she helps several times a week} \\ \pi_{jik}/168 & \text{if she helps once per week} \\ 0.5\pi_{jik}/168 & \text{if she helps less than once per week} \\ 0 & \text{if she never helps} \end{cases} \quad (20)$$

where π_{jik} is the answer to the second question.[22]

Unfortunately, the AHEAD respondents were asked about help from children only if they had an ADL or IADL problem. This feature of the survey design may bias the amount of reported care downwards. However, it is reasonable to assume that parents needing care from children are likely to have an ADL or IADL, and, at the time we constructed our data, there were no better data available.

[22] Alternatively, we could have set up bracketed amounts that are truer to the nature of the first question. Using the brackets is much harder, and it adds precision only for two out of the five categories. These two occur for 949 helpers out of a total of 3144 helpers (30.1%).

10 Appendix 2: Simulation

In order to evaluate the likelihood contributions in equation (16), we must be able to simulate the last term,

$$\iiint\limits_{\substack{\eta_{Xi}\leq\zeta_i \\ i:\widetilde{H}_i=1}} 1\left(\sum_{i:\widetilde{H}_i=1} H_i\left(\eta_{Xi}\right)=\overline{H}\right)\left(\prod_{i:\widetilde{H}_i=1}\frac{1}{\sigma_{\eta X}^2}\phi\left[\frac{\eta_{Xi}}{\sigma_{\eta X}}\right]d\eta_{Xi}\right). \tag{21}$$

Such a term is the probability of a vector of η_{Xi}'s (for those with $\widetilde{H}_i = 1$) conditional on each η_{Xi} being small enough to cause $\widetilde{H}_i = 1$ and also $\sum_{i:\widetilde{H}_i=1} H_i\left(\eta_{Xi}\right) = \overline{H}$. Consider the following GHK-type simulation algorithm:

1) Order $\left\{i : \widetilde{H}_i = 1\right\}$ according some criterion. Let (i) be the ith element of the ordered set. Let $I^* = \#\left\{i : \widetilde{H}_i = 1\right\}$.

2) Initialize $S_{(1)} = 0$ and $P^r = 1$.

3) For each $(i) < I^*$,

a) Let

$$\overline{b}_{(i)} = H_{(i)}^{-1}\left(\max\left\{0, \Psi_{(i)}\right\}\right)$$

be an upper bound where $H_{(i)}^{-1}(\bullet)$ is the inverse of $H_{(i)}\left(\eta_{X(i)}\right)$ implied by equation (17):

$$H_{(i)}^{-1}(x) = \log\left\{\frac{\beta_{1(i)}\mu}{\beta_{2(i)}q}\overline{Q}\left[\max\left(Y_{(i)}^*, Y_{(i)}^{**}\right) - qx\right]\right\}$$

where

$$\begin{aligned} Y_{(i)}^* &= \begin{cases} \sum_{k\in c,s} a_{(i)k}w_{(i)k}\left(1 - L_{(i)k} - \sum_{j\in m,p} t_{j(i)k}\right) & \text{if } i > 0 \\ Y_{(i)} & \text{if } i = 0 \end{cases}, \\ Y_{(i)}^{**} &= \begin{cases} \max\left(Y_{(i)}^*, Y_{(i)} + sY_{(i)}^*\right) & \text{if } i > 0 \\ Y_{(i)} & \text{if } i = 0 \end{cases}, \end{aligned}$$

and

$$\Psi_{(i)} = \overline{H} - S_{(i)} - \sum_{(l)>(i)} \max\left(Y_{(l)}^*, Y_{(l)}^{**}\right)$$

is the least player (i) can contribute; i.e., it is how much she would have to contribute if all remaining players used all resources for $\overline{H} - S_{(i)}$. Note that, if $0 \geq \Psi_{(i)}$,

$$\overline{b}_{(i)} = \log\left(\frac{\beta_{1(i)}\mu p_{Xi}X_{(i)}\overline{Q}}{\beta_{2(i)}q}\right).$$

Also, let

$$\underline{b}_{(i)} = H_{(i)}^{-1}\left(\overline{H} - S_{(i)}\right)$$

be a lower bound.

b) Update

$$P^r = P^r \left[\Phi \left(\frac{\overline{b}_{(i)}}{\sigma_{\eta X}} \right) - \Phi \left(\frac{\underline{b}_{(i)}}{\sigma_{\eta X}} \right) \right].$$

c) Simulate $\eta_{X(i)}$ conditional on $\underline{b}_{(i)} \leq \eta_{X(i)} \leq \overline{b}_{(i)}$ as

$$\eta^r_{X(i)} = \sigma_{\eta X} \Phi^{-1} \left\{ \left[\Phi \left(\frac{\overline{b}_{(i)}}{\sigma_{\eta X}} \right) - \Phi \left(\frac{\underline{b}_{(i)}}{\sigma_{\eta X}} \right) \right] u^r + \Phi \left(\frac{\underline{b}_{(i)}}{\sigma_{\eta X}} \right) \right\}$$

where $u^r \sim U(0,1)$.

d) Compute $H_{(i)} \left(\eta^r_{X(i)} \right)$ using $\eta^r_{X(i)}$ and equation (17).

e) Compute $S_{(i+1)} = S_{(i)} + H_{(i)} \left(\eta^r_{X(i)} \right)$.

4) For $(i) = I^*$,

a) Let

$$\eta^r_{X(I^*)} = H^{-1}_{(I^*)} \left(\overline{H} - S_{(I^*)} \right).$$

b) Update

$$P^r = \frac{P^r}{\sigma_{\eta X}} \phi \left[\frac{\eta_{X(I^*)}}{\sigma_{\eta X}} \right].$$

5) P^r is our simulator of equation (21). Note that, if there is only one player who satisfies the conditions in the integral in equation (21), then the equation becomes

$$\frac{1}{\sigma^2_{\eta X}} \phi \left[\frac{H^{-1}_{(i)} \left(\overline{H} \right)}{\sigma_{\eta X}} \right]$$

which can be evaluated analytically.

Consider how to interpret the GHK algorithm as an importance sampling simulator. Rewrite equation (21) as

$$\begin{aligned} & \iiint\limits_{\substack{\eta_{X(i)} \leq \zeta_i \\ \sum_{(i)=1}^{I^*} H_{(i)}\left(\eta_{X(i)}\right) = \overline{H}}} f(\eta_X)\, d\eta_X \\ = & \iiint\limits_{\substack{\eta_{X(i)} \leq \zeta_i \\ \sum_{(i)=1}^{I^*} H_{(i)}\left(\eta_{X(i)}\right) = \overline{H}}} \frac{f(\eta_X)}{g(\eta_X)} g(\eta_X)\, d\eta_X \end{aligned}$$

where $\eta_X = \left(\eta_{X(1)}, \eta_{X(2)}, .., \eta_{X(I)}\right)$,

$$
\begin{aligned}
f(\eta_X) &= \prod_{(i)=1}^{I^*} \frac{1}{\sigma^2_{\eta X}} \phi\left[\frac{\eta_{X(i)}}{\sigma_{\eta X}}\right] \prod_{(i)=1}^{I^*-1} 1\left(\underline{b}_{(i)} \leq \eta_{X(i)} \leq \overline{b}_{(i)}\right) \\
g(\eta_X) &= \prod_{(i)=1}^{I^*-1} \frac{\frac{1}{\sigma^2_{\eta X}} \phi\left[\frac{\eta_{X(i)}}{\sigma_{\eta X}}\right]}{\Phi\left(\frac{\overline{b}_{(i)}}{\sigma_{\eta X}}\right) - \Phi\left(\frac{\underline{b}_{(i)}}{\sigma_{\eta X}}\right)} 1\left(\underline{b}_{(i)} \leq \eta_{X(i)} \leq \overline{b}_{(i)}\right),
\end{aligned}
$$

which implies that

$$
\frac{f(\eta_X)}{g(\eta_X)} = \frac{1}{\sigma^2_{\eta X}} \phi\left[\frac{\eta_{X(I)}}{\sigma_{\eta X}}\right] \prod_{(i)=1}^{I^*-1} \left[\Phi\left(\frac{\overline{b}_{(i)}}{\sigma_{\eta X}}\right) - \Phi\left(\frac{\underline{b}_{(i)}}{\sigma_{\eta X}}\right)\right].
$$

Note that we are simulating $E\frac{f(\eta_X)}{g(\eta_X)}$ with errors η_X simulated from density $g(\eta_X)$. The fact that we can write our simulator as an importance sampling simulator means that it is unbiased.

We want to minimize the variance of our simulator, especially because we are using maximum simulated likelihood estimation rather than the method of simulated moments. First, we can improve on the variance of our simulator by using antithetic acceleration. Second, we can use a criterion for ordering $\left\{i : \widetilde{H}_i = 1\right\}$ in Step 1 of the algorithm that reduces the variance. Consider a case with $I^* = 2$. In Figure 2, the $\overline{H}$ curve represents those values of $\left(\eta_{X(1)}, \eta_{X(2)}\right)$ that result in total formal care expenditures of $\overline{H}$. Note that the curve asymptotes at $\underline{b}_{(1)}$ and $\overline{b}_{(1)}$. At $\underline{b}_{(1)}$, as $\eta_{X(2)}$ increases, $H_{(2)}$ approaches 0 (and reaches 0); thus $\eta_{X(1)}$ must converge to that value such that child (1) will provide $\overline{H}$. On the other hand, as $\eta_{X(2)}$ decreases, $H_{(2)}$ converges to the income of child (2); thus $\eta_{X(1)}$ must converge to that value such that child (1) will provide $\overline{H}$ minus the income of child (2). Our GHK algorithm first computes the probability that $\underline{b}_{(1)} \leq \eta_{X(1)} \leq \overline{b}_{(1)}$. Next the GHK algorithm simulates a value of $\eta_{X(1)}$ conditional on $\underline{b}_{(1)} \leq \eta_{X(1)} \leq \overline{b}_{(1)}$. Then it computes the probability that $\eta_{X(2)}$ is such that the simulated values of $\eta_{X(1)}$ and $\eta_{X(2)}$ are on the $\overline{H}$ curve. The simulator is the product of the two probabilities. The variance of the simulator is proportional to the variance of the second probability as a function of the simulated value of $\eta_{X(1)}$. Thus, we should arrange $\left\{i : \widetilde{H}_i = 1\right\}$ in descending order of the variance of the contribution to the simulator with respect to the elements of η_X that precede it.

Such an ordering rule is too expensive to evaluate and may depend upon realizations of early elements of η_X. Instead, we want an alternative rule that approximates the rule described above but that is easy to employ and does not depend upon realizations of early elements of η_X. A simple example of such a rule is to order $\left\{i : \widetilde{H}_i = 1\right\}$ in ascending order with respect to

$$\left| \frac{\phi\left[\frac{\overline{b}_i}{\sigma_{\eta X}}\right] - \phi\left[\frac{b_i^*}{\sigma_{\eta X}}\right]}{\Phi\left(\frac{\overline{b}_i}{\sigma_{\eta X}}\right) - \Phi\left(\frac{b_i^*}{\sigma_{\eta X}}\right)} \right|$$

where

$$b_i^* = H_i^{-1}\left(\overline{H}\right).$$

We also need to simulate terms like the second term in equation (**??**):

$$\int_{\eta_{Xi} \geq \zeta_i} \prod_{j \in m,p} \Pr\left[t_{ji} \mid \widetilde{H}_i = 0, \varepsilon_{Xi}\right]^{a_{0j}} \Pr\left[L_i \mid \widetilde{H}_i = 0, \varepsilon_{Xi}\right] \frac{1}{\sigma_{\eta X}^2} \phi\left[\frac{\eta_{Xi}}{\sigma_{\eta X}}\right] d\eta_{Xi}$$

But this requires just drawing $\eta_{Xi} \mid \eta_{Xi} \geq \zeta_i$ and then evaluating the integrand conditional on the draw of η_{Xi}.

Finally, we need to be able to simulate

$$\Pr\left[u_0 \mid \widetilde{H}_0, t_0\right] = \int \cdots \int \Pr\left[u_0 \mid \eta_{X0}, \eta_{t0}\right] f\left[\eta_{X0}, \eta_{t0} \mid \widetilde{H}_0, t_0\right] d\eta_{X0} d\eta_{t0}.$$

This is a straightforward application of GHK.

11 Appendix 3: Correction for Measurement Error in Specification Tests

Let $y_i^* \sim iidF$, let

$$y_i = k1\left(c_k \leq y_i^* < c_{k+1}\right),$$

and let

$$\widehat{y}_i^* = \sum_k g\left(c_k, c_{k+1}\right) 1\left(y_i = k\right).$$

What are the moments of $z_i^* = \widehat{y}_i^* - y_i^*$?

$$\begin{aligned} Ez_i^* &= E\sum_k g\left(c_k, c_{k+1}\right) 1\left(y_i = k\right) - y_i^* \\ &= \sum_k g\left(c_k, c_{k+1}\right) \Pr\left(y_i = k\right) - Ey_i^* \\ &= \sum_k g\left(c_k, c_{k+1}\right) \left[F\left(c_{k+1}\right) - F\left(c_k\right)\right] - Ey_i^*, \end{aligned}$$

and

$$\begin{aligned}
Var\left(z_i^*\right) &= Var\left[\sum_k g\left(c_k, c_{k+1}\right) 1\left(y_i = k\right) - y_i^*\right] \\
& E\left[\sum_k g\left(c_k, c_{k+1}\right) 1\left(y_i = k\right) - y_i^* - Ez_i^*\right]^2 \\
&= \int \left[\sum_k g\left(c_k, c_{k+1}\right) 1\left(y_i = k\right) - y_i^* - Ez_i^*\right]^2 dF\left(y_i^*\right) \\
&= \sum_k \int_{c_k}^{c_{k+1}} \left[g\left(c_k, c_{k+1}\right) - y_i^* - Ez_i^*\right]^2 dF\left(y_i^*\right).
\end{aligned}$$

If $y_i^* \sim iidU\left(0,1\right)$ and

$$g\left(c_k, c_{k+1}\right) = \frac{c_k + c_{k+1}}{2},$$

then

$$F\left(c_{k+1}\right) - F\left(c_k\right) = c_{k+1} - c_k,$$

$$\begin{aligned}
Ez_i^* &= \sum_k \frac{c_k + c_{k+1}}{2}\left(c_{k+1} - c_k\right) - \frac{1}{2} \\
&= \sum_k \frac{c_{k+1}^2 - c_k^2}{2} - \frac{1}{2} = 0,
\end{aligned}$$

and

$$\begin{aligned}
Var\left(z_i^*\right) &= \sum_k \int_{c_k}^{c_{k+1}} \left[\frac{c_k + c_{k+1}}{2} - y_i^*\right]^2 dy_i^* \\
&= \sum_k \int_{c_k}^{c_{k+1}} \left[\frac{c_k + c_{k+1}}{2} - y_i^*\right]^2 \frac{c_{k+1} - c_k}{c_{k+1} - c_k} dy_i^* \\
&= \sum_k \frac{\left(c_{k+1} - c_k\right)^3}{12}.
\end{aligned}$$

In the data, the values of c are (0,1/7,1/7,1,1). Thus,

$$\begin{aligned}
Var\left(z_i^*\right) &= \sum_k \frac{\left(c_{k+1} - c_k\right)^3}{12} \\
&= \frac{\left(\frac{1}{7}\right)^3 + \left(\frac{6}{7}\right)^3}{12} \\
&= .229^2.
\end{aligned}$$

We multiply $Var\left(z_i^*\right)$ by $\left(1.6/168\right)^2$ where 1.6 is the average value of π in equation (20) in the data. Thus, $\sigma_m = \left(1.6/168\right) \cdot .229 = .002$.

12 Appendix 4: Simulating Policy Experiment Effects

Consider the general problem where we have a set of agents indexed by i, each with a utility function

$$U_i(v_i, P)$$

with choice variables v_i and some (government) policy variable or environmental characteristic P. In general, we can solve for the derivatives of choice variables with respect to policy variables as follows. Let v be the $m-$vector of choice variables, let ε be the $m-$vector of errors in the model, and let the set of first order conditions be written as

$$\underset{m_r\times m}{D_n'(\varepsilon)}\left[\underset{m\times 1}{\varepsilon}-\underset{m\times 1}{\psi}\left(\underset{m\times 1}{v},P\right)\right]=0 \tag{22}$$

where $D_n(\varepsilon)$ is a matrix that pulls the m_r rows of $\varepsilon-\psi(v,P)$ corresponding to interior solutions of first order conditions (conditional on ε) for family n. Conditional on ε, we can differentiate equation (22) to get

$$\begin{aligned} 0 &= \underset{m_r\times m}{D_n'(\varepsilon,P)}\left[\underset{m\times m}{\psi_v}\ \underset{m\times m_r}{D_n(\varepsilon,P)}\underset{m_r\times m}{D_n'(\varepsilon,P)}\underset{m\times 1}{dv}+\underset{m\times 1}{\psi_P}\,dP\right] \\ \Rightarrow\ D_n'(\varepsilon,P)\frac{dv}{dP} &= -\left[\underset{m_r\times m}{D_n'(\varepsilon,P)}\ \underset{m\times m}{\psi_v}\ \underset{m\times m_r}{D_n(\varepsilon,P)}\right]^{-1}\left[\underset{m_r\times m}{D_n'(\varepsilon,P)}\,\underset{m\times 1}{\psi_P}\right]. \end{aligned}$$

Now we are interested in

$$E\frac{dv}{dP}=\int\cdots\int D_n'(\varepsilon,P)\frac{dv}{dP}f(\varepsilon)\,d\varepsilon \tag{23}$$

where $f(\varepsilon)$ is the joint density of ε. Note that we do not have to worry about the term associated with $\partial D_n(\varepsilon,P)/\partial P$ because the relevant term is

$$\frac{\partial D_n(\varepsilon,P)}{\partial P}v(\varepsilon,P)\,f(\varepsilon)$$

which is zero because $v(\varepsilon,P)=0$ at values of (ε,P) where $D_n(\varepsilon,P)$ changes.

We need to simulate equation (23) in such a way that we "oversample" from that part of the support of ε where $\frac{dv}{dP}\neq 0$. Write equation (23) as

$$E\frac{dv}{dP}=E_k\frac{dv}{dP}=\underset{\widetilde{\varepsilon}_k}{\int\cdots\int}\int_{\varepsilon_k}D_n'(\varepsilon,P)\frac{dv}{dP}f(\varepsilon)\,d\varepsilon_k d\widetilde{\varepsilon}_k$$

where $E_k\frac{dv}{dP}$ rearranges the order of integration in equation (23) so that the innermost integral is over the kth element of ε and $\widetilde{\varepsilon}_k=(\varepsilon_1,..,\varepsilon_{k-1},\varepsilon_{k+1},..,\varepsilon_m)'$ is the $(m-1)-$vector of ε excluding ε_k. Note that

$$E\frac{dv}{dP}=E_k\frac{dv}{dP}\ \forall k.$$

Then we can write equation (23) as

$$\begin{aligned} E\frac{dv}{dP} &= \frac{1}{m}\sum_{k=1}^{m} E_k \frac{dv}{dP} \qquad (24) \\ &= \frac{1}{m}\sum_{k=1}^{m} \underbrace{\int \cdots \int}_{\widetilde{\varepsilon}_k} \int_{\varepsilon_k} D_n'(\varepsilon, P)\frac{dv}{dP} f(\varepsilon)\, d\varepsilon_k d\widetilde{\varepsilon}_k. \end{aligned}$$

Let

$$A_k(\widetilde{\varepsilon}_k) = \{\varepsilon_k : v(\varepsilon, P) > 0 \mid \widetilde{\varepsilon}_k\}$$

and

$$B_k(\widetilde{\varepsilon}_k) = \{\varepsilon_k : v(\varepsilon, P) = 0 \mid \widetilde{\varepsilon}_k\}.$$

Then equation (24) can be written as

$$\begin{aligned} &= \frac{1}{m}\sum_{k=1}^{m} \underbrace{\int \cdots \int}_{\widetilde{\varepsilon}_k} \left[\int_{A_k(\widetilde{\varepsilon}_k)} D_n'(\varepsilon, P)\frac{dv}{dP} f(\varepsilon)\, d\varepsilon_k d\widetilde{\varepsilon}_k \right. \\ &\quad \left. + \int_{B_k(\widetilde{\varepsilon}_k)} D_n'(\varepsilon, P)\frac{dv}{dP} f(\varepsilon)\, d\varepsilon_k d\widetilde{\varepsilon}_k \right]. \end{aligned}$$

It can be simulated as

$$\begin{aligned} &\frac{1}{mR}\sum_{r=1}^{R}\sum_{k=1}^{m} \left[D_n'\left(\varepsilon_{A_k}^r, P\right) \frac{dv\left(\varepsilon_{A_k}^r, P\right)}{dP} \Pr\left(\varepsilon_k \in A_k\left(\widetilde{\varepsilon}_k^r\right) \mid \widetilde{\varepsilon}_k^r\right) \right. \qquad (25) \\ &\left. + D_n'\left(\varepsilon_{B_k}^r, P\right) \frac{dv\left(\varepsilon_{B_k}^r, P\right)}{dP} \Pr\left(\varepsilon_k \in B_k\left(\widetilde{\varepsilon}_k^r\right) \mid \widetilde{\varepsilon}_k^r\right) \right] \end{aligned}$$

where $\varepsilon_{A_k}^r$ is a draw from $f(\cdot)$ conditional on the kth element $\varepsilon_{A_k k}^r \in A_k(\widetilde{\varepsilon}_k^r)$ and $\varepsilon_{B_k k}^r$ is a draw from $f(\cdot)$ conditional on the kth element $\varepsilon_{B_k k}^r \in B_k(\widetilde{\varepsilon}_k^r)$. In practice, one uses the following algorithm to simulate equation (25):

For each draw $r = 1, 2, .., R$:

1) Draw ε^r from $f(\cdot)$.

2) For each $k = 1, 2, .., m$:

a) Pull out $\widetilde{\varepsilon}_k^r$ from ε^r;

b) Find the boundary along ε_k between $A_k(\widetilde{\varepsilon}_k^r)$ and $B_k(\widetilde{\varepsilon}_k^r)$ and call it ε_k^*;

c) Compute $F_k(\varepsilon_k \mid \widetilde{\varepsilon}_k^r)$ analytically and assign appropriate probabilities to $\Pr(\varepsilon_k \in A_k(\widetilde{\varepsilon}_k^r) \mid \widetilde{\varepsilon}_k^r)$ and $\Pr(\varepsilon_k \in B_k(\widetilde{\varepsilon}_k^r) \mid \widetilde{\varepsilon}_k^r)$;

d) Simulate $\varepsilon_{A_k}^r$ and evaluate $dv\left(\varepsilon_{A_k}^r, P\right)/dP$;

e) Simulate $\varepsilon_{B_k}^r$ and evaluate $dv\left(\varepsilon_{B_k}^r, P\right)/dP$;

f) Plug the simulated values of $dv\left(\varepsilon_{A_k}^r, P\right)/dP$ and $dv\left(\varepsilon_{B_k}^r, P\right)/dP$ into equation (25) and sum;

3) Divide by mR.

The details for this application are provided at

http://faculty.virginia.edu/stevenstern/resint/ltcstf/welfaresimul.pdf.

13 References

References

[1] Aguirregabiria, Victor and Pedro Mira (2001). "Sequential Estimation of Dynamic Discrete Games with Multiple Equilibria." Boston University Working Paper, December.

[2] Barber, Clifton E. (1989). "Burden and Family Care of the Elderly." in *Aging and the Family.* Stephen J. Bahr and Evan T. Peterson (eds.). Lexington, MA: Lexington Books.

[3] Bernheim, Douglas, Andrei Shleifer, and Lawrence Summers (1985). "The Strategic Bequest Motive." *Journal of Political Economy.* 93(6): 1045-76.

[4] Boaz, Rachel F. and Jianxun Hu (1997). "Determining the Amount of Help Used by Disabled Elderly Persons at Home: The Role of Coping Resources." *Journals of Gerontology, Series B: Psychological Sciences and Social Sciences.* 52B: S317-S324.

[5] Boersch-Supan, Axel, Laurence Kotlikoff, and John Morris (1988). "The Dynamics of Living Arrangements of the Elderly." NBER Working Paper 2787.

[6] Bureau of Economic Analysis (1999). http://www.bea.doc.gov/bea/regional/data.htm.

[7] Byrne, David, Michelle Goeree, Bridget Hiedemann, and Steven Stern (2003). "Income Eligibility Criteria for Medicaid." http://faculty.virginia.edu/stevenstern/resint/ltcstf/medicaideligibility.pdf.

[8] Byrne, David, Michelle Goeree, Bridget Hiedemann, and Steven Stern (2005). "Supplementary Tables for 'Formal Home Health Care, Informal Care, and Family Decision-Making." http://faculty.virginia.edu/stevenstern/resint/ltcstf/hrssupplement.html.

[9] Cantor, Marjorie H. (1983). "Strain Among Caregivers: A Study of Experience in the United States." *The Gerontologist.* 23: 597-604.

[10] Checkovitch, Tennille and Steven Stern (2002). "Shared Caregiving Responsibilities of Adult Siblings with Elderly Parents." *Journal of Human Resources.* forthcoming.

[11] Congressional Research Service: Subcommittee on Health and the Environment (1993). *Medicaid Source Book: Background Data and Analysis.* Washington, D.C.: U.S. Government Printing Office.

[12] Couch, Kenneth A., Mary C. Daly, and Douglas A. Wolf (1999). "Time? Money? Both? The Allocation of Resources to Older Parents." *Demography.* 36(2): 219-232.

[13] Cutler, David and Louise Sheiner (1993). "Policy Options for Long-Term Care." *NBER Working Paper 4302.*

[14] Diwan, Sadhna, Cathie Berger, and Edith Manns (1997). "Composition of the Home Care Service Package: Predictors of Type, Volume, and Mix of Services Provided to Poor and Frail Older People." *The Gerontologist.* 37: 169-181.

[15] Engers, Maxim and Steven Stern (2002). "Long-Term Care and Family Bargaining." *International Economic Review.* 43(1): 73-114.

[16] Ettner, Susan L. (1996). "The Opportunity Costs of Elder Care." *Journal of Human Resources.* 31(1): 189-205.

[17] Frankfather, D., M. J. Smith, and Francis G. Caro (1981). *Family Care of the Elderly: Public Initiatives and Private Obligations.* Lexington, MA: Lexington Books.

[18] Gourieroux, C., A. Monfort, E. Renault, and A. Trognon (1987). "Generalized Residuals." *Journal of Econometrics.* 34(1/2): 5-32.

[19] Gruber, Jonathan and Aaron Yelowitz (1999). "Public Health Insurance and Private Savings." *Journal of Political Economy.* 107(6): 1250-1274.

[20] Hajivassiliou, Vassilis, Daniel McFadden, and Paul Ruud (1994). " Simulation of Multivariate Normal Rectangle Probabilities and Their Derivatives: Theoretical and Computational Results." Yale University, Cowles Foundation Discussion Paper: 1021R.

[21] Hardwick, Susan E., P. Jennifer Pack, Elizabeth A. Donohue, and Kristen J. Aleksa (1994). A*cross the States: Profiles of Long-Term Care Systems 1994.* Wash. D.C.: American Association of Retired Persons.

[22] Hausman, Jerry (1985). "The Econometrics of Nonlinear Budget Sets." *Econometrica.* 53(6): 1255-1282.

[23] Hiedemann, Bridget and Steven Stern (1999). "Strategic Play Among Family Members When Making Long-Term Care Decisions." *Journal of Economic Behavior and Organization.* 40(1): 29-57.

[24] Hoerger, Thomas J., Gabriel A. Picone, and Frank A. Sloan (1996). "Public Subsidies, Private Provision of Care and Living Arrangements of the Elderly." *Review of Economics and Statistics.* 78(3): 428-440.

[25] Horowitz, Amy (1985). "Family Caregiving to the Frail Elderly." *Annual Review of Gerontology and Geriatrics.* 6: 194-246.

[26] Johnson, C. L. (1983). "Dyadic Family Relations and Social Support." *The Gerontologist.* 23: 377-383.

[27] Johnson, C. L. and D. J. Catalano (1981). "Childless Elderly and Their Family Supports." *The Gerontologist.* 21: 612-618.

[28] Lee, G., J. Dwyer and R. Coward (1990). "Residential Location and Proximity to Children Among Impaired Elderly Parents." *Rural Sociology.* 55(4): 579-589.

[29] Liu, Korbin, Pamela Doty, and Kenneth Manton (1990). "Medicaid Spend-down in Nursing Homes." *The Gerontologist.* 30(1): 7-9.

[30] Macken, C. (1986). "A Profile of Functionally Impaired Elderly Persons Living in the Community." *Health Care Financing Review.* 7: 33-50.

[31] Manton, Kenneth G., Larry Corder, and Eric Stallard (1997). "Chronic Disability Trends in Elderly United States Populations: 1982-1994." *Proceedings of the National Academy of Sciences.* 94: 2593-2598.

[32] Matthews, Sarah H. and Tena Tarler Rosner (1988). "Shared Filial Responsibility: The Family as the Primary Caregiver." *Journal of Marriage and the Family.* 50: 185-195.

[33] McGarry, Kathleen (1999). "Inter Vivos Transfers and Intended Bequests." *Journal of Public Economics.* 73(3): 321-51.

[34] Miller, Baila and Andrew Montgomery (1990). "Family Caregivers and Limitations in Social Activities." *Research on Aging.* 12: 72-93.

[35] Morrison, Peter A. (1990). "Demographic Factors Reshaping Ties to Family and Place." *Research on Aging.* 12: 399-408.

[36] National Center for Health Statistics (1994a). *Advance Data From Vital and Health Statistics, No. 247.* Hyattsville, Md.

[37] National Center for Health Statistics (1994b). *Advance Data From Vital and Health Statistics, No. 256.* Hyattsville, Md.

[38] National Center for Health Statistics (1996a). *Health, United States, 1995.* Hyattsville, Md.

[39] National Center for Health Statistics (1996b). *Advance Data from Vital and Health Statistics, No. 309.* Hyattsville, Md.

[40] Noelker, Linda S. and Robert W. Wallace (1985). "The Organization of Family Care for the Impaired Elderly." *Journal of Family Issues.* 6: 3-44.

[41] Norgard, Theresa and Willard Rodgers (1997). "Patterns of In-Home Care Among Elderly Black and White Americans." *Journals of Gerontology, Series B: Psychological Sciences and Social Sciences.* 52B: 93-101.

[42] Pezzin, Liliana E. and Barbara Steinberg Schone (1997). "The Allocation of Resources in Intergenerational Households: Adult Children and Their Elderly Parents." *American Economic Review.* 87(2): 460-464.

[43] Pezzin, Liliana E. and Barbara Steinberg Schone (1999). "Intergenerational Household Formation, Female Labor Supply and Informal Caregiving: A Bargaining Approach." *Journal of Human Resources*. 34(3): 475-503.

[44] Schneider, Andy, Kristen Fennel, and Patricia Keenan (1999). *Medicaid Eligibility for the Elderly*, Prepared for The Kaiser Commission on Medicaid and the Uninsured.

[45] Schoonover, Claire B., Elaine M. Brody, Christine Hoffman, and Morton H. Kleban (1988). "Parent Care and Geographically Distant Children." *Research on Aging*. 10: 472-492.

[46] Shanas, Ethel (1979a). "Social Myth as Hypothesis: The Case of the Family Relations of Old People." *The Gerontologist*. 19: 3-9.

[47] Shanas, Ethel (1979b). "The Family as a Social Support System in Old Age." *The Gerontologist*. 19: 169-174.

[48] Shanas, Ethel (1980). "Older People and Their Families: The New Pioneers." *Journal of Marriage and the Family*. 42: 9-15.

[49] Sloan, Frank A., Gabriel Picone, and Thomas J. Hoerger (1997). "The Supply of Children's Time To Disabled Elderly Parents." *Economic Inquiry*. 35(2): 295-308.

[50] Sloan, Frank A. and May W. Shayne (1993). "Long-term care, Medicaid, and the Impoverishment of the Elderly." *The Milbank Quarterly*. 71(4): 575-625.

[51] Spector, William D., John A. Fleishman, Liliana E. Pezzin, and Brenda C. Spillman (1999). "The Characteristics of Long-Term Care Users." *Institute of Medicine Report on the Quality of Long-Term Care*. forthcoming.

[52] Stern, Steven (1994). "Two Dynamic Discrete Choice Estimation Problems and Simulation Method Solutions." *Review of Economics and Statistics*. 76: 695-702.

[53] Stern, Steven (1995). "Estimating Family Long-Term Care Decisions in the Presence of Endogenous Child Characteristics." *The Journal of Human Resources*. 30: 551-580.

[54] Stern, Steven (1996). "Measuring Child Work and Residence Adjustments to Parent's Long-Term Care Needs." *The Gerontologist*. 30: 76-87.

[55] Stoller, Eleanor Palo and L. L. Earl (1983). "Help with the Activities of Everyday Life: Sources of Support for the Non-Institutionalized Elderly." *The Gerontologist*. 23: 64-70.

[56] Streib, G. F. (1983). "The Frail Elderly: Research Dilemmas and Opportunities." *The Gerontologist*. 23: 40-44.

[57] U.S. Congress. House Committee on Ways and Means (1993). *The Green Book: Background Material and Data on Programs within the Jurisdiction of the Committee on Ways and Means.* Washington, D.C.: U.S. Government Printing Office.

[58] US. Department of Health and Human Services, Health Care Financing Administration (1992). *State Profile Data System: Characteristics of Medicaid State Programs, Volume 1.* Washington, D.C.

[59] US. Department of Health and Human Services, Health Care Financing Administration (2000). *2000 National Health Expenditures.* http://www.hcfa.gov/stats/NHE-OAct/.

[60] White-Means, Shelly I.(1997). "The Demands of Persons with Disabilities for Home Health Care and the Economic Consequences for Informal Caregivers." *Social Science Quarterly.* 78(4): 955-972.

[61] Wiener, Joshua M. and David Stevenson (1999). *Long-Term Care for the Elderly and State Health Policy.* Washington, D.C.: The Urban Institute.

[62] Wolf, Douglas, and Beth Soldo (1988). "Household Composition Choices of Older Unmarried Women." *Demography.* 25(3): 387-403.

14 Tables and Figures

Table 1
Dropped Household Observations

Total Households	6047
More than Five Children	625
Missing Child Variable	1008
Missing Parent Variable	108
Working Respondent	270
Respondents Helping Each Other	25
Small Minority Groups	350
Coding Errors	78
Sample Size	3583

Table 2
Selected Characteristics of Respondents

Characteristic	Male	Female
Age	76.73	76.30
Education	11.73	11.80
Black	0.07	0.10
Living Children	2.06	2.02
Married	0.72	0.42
Number of ADL problems	0.52	0.71
At Least 1 ADL problem	0.23	0.31
Number of IADL problems	0.36	0.34

Table 3
Child Characteristics of Respondents

Characteristic	Mean
Age	47.01
Male	0.490
Education	13.98
Married	0.698
Number of Children	1.985
Live with Parent	0.06
Live More Than 10 Miles from Parent	0.62
Imputed Weekly Wage	$452

Note: We also observe bracketed time spent helping respondents and labor force participation of the child and spouse of the child.

Table 4 Ln Wage Estimates			
Variable	Estimate	Variable	Estimate
Constant	0.028 (0.072)	Male	0.099** (0.030)
Years of Schooling, < High School Degree	0.035** (0.006)	Married	0.028 (0.029)
High School Diploma	0.540** (0.052)	White	0.066** (0.022)
Some College	0.680** (0.053)	Male$*$Married	0.090** (0.042)
College Degree	0.978** (0.053)	Male$*$White	0.022 (0.033)
> College Degree	1.086** (0.054)	Married$*$White	-0.035 (0.032)
Age	0.066** (0.002)	Male$*$Married$*$White	0.093** (0.045)
Age^2	-0.001** (0.000)		
$R^2 = 0.34$			

Notes:

1. The dependent variable is ln wage.
2. The numbers in parentheses are standard errors.
3. Double starred items are significant at the 5% level.
4. The education variables refer to highest education level attained. The first variable is a slope conditional on not finishing high school, and the others are dummy variables.

Table 5. Characteristics of Care Provision for Families of Various Sizes								
Family Type	No Children		Number of Children †					Total
	Single	Married	1	2	3	4	5	
Share of All Families (Percent)	17.8	3.7	20.8	27.8	16.9	9.0	3.9	100
Share of Type Receiving Any Care	5.6	38.1	26.3	24.7	25.7	26.1	22.9	22.3
Formal Care *	100	9.8	21.8	12.9	12.2	8.2	3.1	17.8
Informal Care *		98.0	88.3	93.5	96.8	100	100	89.9
Both Formal and Informal Care *		7.8	10.2	6.5	9.0	8.2	3.1	7.7
Kids Help Pay for Care ♮			11.6	12.5	5.3	0	0	8.7
Spouse Provides Informal Care ♯		100	48.9	62.9	63.6	63.5	68.8	62.6
Ave Hours / Week		26.8	25.8	25.8	24.3	27.1	34.4	26.2
Children Provide Informal Care ♯			54.0	40.1	43.7	42.4	40.6	41.7
Ave Hours / Week			21.3	23.7	27.5	21.9	16.8	23.5
Multiple Children Care				9.7	16.7	19.4	23.1	14.4
Kids and Spouse ♯			2.9	3.0	7.3	5.9	9.4	4.6
† Includes families with single and married respondents.								
* As share of families with respondents receiving any care.								
♮ As share of families with respondents receiving formal care.								
♯ As share of families with respondents receiving informal care.								

Note: Children and their spouses are aggregated into one caregiver.

Table 6 Estimates of Model With No Covariates			
Variable	Estimate	Variable	Estimate
$\log \alpha$	-0.719 (1.596)	γ	-10.390** (1.458)
$\log \mu$	-5.476** (1.567)	$\log(-\beta_0)$	8.222** (0.834)
$\log Z$	-1.084 (1.606)	$\log \sigma_{\eta X}$	0.108** (0.032)
$\log \beta_{10}$	-0.766** (0.057)	$\log \sigma_{\eta L}$	0.225** (0.083)
β_{40}	-1.563** (0.051)	$\log \sigma_{\eta t}$	0.189** (0.023)
$\log \beta_2$	0.000 Restricted	$\log \sigma_u$	8.039** (0.928)
$\log \beta_{1i}$	-0.431** (0.074)	ρ_L	0.900** See note 2
$\log \beta_{3i}$	0.340** (0.053)	ρ_t	0.900** See note 2
β_{4i}	-2.189** (0.078)		

Notes:

1. Numbers in parentheses are standard errors. Single starred items are significant at the 10% level, and double starred items are significant at the 5% level.

2. $\widehat{\rho}_L$ and $\widehat{\rho}_t$ are set equal to

$$\widehat{\rho}_r = 1.8\frac{\exp\{\lambda_r\}}{1+\exp\{\lambda_r\}} - .9$$

for $r = L, t$ to insure nice properties of the model. The estimates of λ are $(17.85, 11.84)$ which implies that the standard errors of $\widehat{\rho}_L$ and $\widehat{\rho}_t$ are trivial.

3. The log likelihood value is -15428.1.

Table 7

Estimates with Covariation in $\log \alpha$ and β_4

Variable	Estimate on $\log \alpha$	Estimate on $\log Z$	Estimate on β_4	Estimate on $\log \beta_1$	Estimate on $\log \beta_3$
Parent Characteristics					
Constant	-5.089** (0.554)	-3.203** (0.361)	-4.186** (0.672)	-0.722** (0.159)	
Age/100	-0.864** (0.074)	-3.121** (0.237)	0.913 (0.834)		
Education	-0.020** (0.006)				
White	0.115 (0.230)	-0.009 (0.190)	-0.236 (0.296)		
Married		0.331** (0.093)			
# ADL Problems	-0.165** (0.038)	-0.287** (0.037)	-0.280** (0.109)		
Mother	0.353** (0.156)	0.184 (0.144)	0.116 (0.185)		
Spouse Characteristics					
Age/100	2.599** (0.103)				
# ADL Problems	-0.095* (0.057)				
Child Characteristics					
Constant	-0.752** (0.347)		-5.333** (1.020)	1.113** (0.125)	0.346** (0.056)
Age/100	-0.918** (0.191)		9.933** (1.393)		
Male	0.389** (0.170)		-1.262 (1.167)		
Biological	0.110 (0.151)		-0.376 (0.633)		
Biological*Male	-0.449** (0.214)		0.851 (1.159)		
Education	0.002 (0.016)		-0.178** (0.050)		
Married	0.401* (0.210)		-11.539** (2.138)		
# Kids	0.053** (0.023)		-0.317** (0.070)		
Oldest	-0.048 (0.133)		0.245 (0.235)		

Table 7 (continued) Estimates with Covariation in $\log \alpha$ and β_4			
Variable	Estimate	Variable	Estimate
$\log \mu$	-10.153** (0.472)	$\log \sigma_{\eta t}$	0.890** (0.085)
γ	-5.846** (0.617)	$\log \sigma_u$	11.974** (0.895)
$\log \beta_0$	12.155** (0.785)	ρ_L	0.900
$\log \sigma_{\eta X}$	-0.037 (0.064)	ρ_t	0.900
$\log \sigma_{\eta L}$	0.221** (0.009)		

Notes:

1. The numbers in parentheses are standard errors. Single starred items are significant at the 10% level, and double starred items are significant at the 5% level.

2. The terms $\widehat{\rho}_L$ and $\widehat{\rho}_t$ are set equal to

$$\widehat{\rho}_r = 1.8 \frac{\exp\{\lambda_r\}}{1 + \exp\{\lambda_r\}} - .9$$

   for $r = L, t$ to insure nice properties of the model. Estimates without reported standard errors have standard errors that are trivial.

3. The log likelihood value is -14512.0.

Table 8
Moments of Behavior

	Parent or Spouse		Children	
Variable	Mean	Std. Dev	Mean	Std. Dev
$\log \alpha$	-3.859	0.325	-6.337	0.380
$\log \beta_1$	-0.956	0.338	1.886	0.512
$\log \beta_3$	0.080	0.146	0.329	0.077
β_4	-3.787	0.305	-13.852	4.648
Utility	6.348	10.887	6.327	11.070
logHealth	-5.510	0.533		

Table 9
Relative Effects of Informal Care and ADLs

	$\alpha \cdot 1000$	$\Delta Q/Q$ (t: 0 to 0.12)	$\Delta Q/Q$ (ADL: 0-1)
Individual 1	22.768	0.023	-0.287
Individual 2	2.027	0.189	-0.287

Notes: "Representative individuals:"

1. Individual 1 is a 76 year old, single, white woman with 11 years of education, 1 ADL problem, and a 47 year old, married, biological daughter. This child, who is not her oldest child, has 14 years of education and 2 children; and

2. Individual 2 is a 76 year old, married, white woman with 11 years of education, and 1 ADL problem, and no children. Her husband is also 76 years old with 1 ADL problem.

Table 10 Decomposition of Child Gender Effects on Pr $[t > 0]$						
	# Obs	All Effects	Just Wage Effect	Just Quality of Care Effect	Just Burden Effect	No Effects
One Child Families						
Single Daughters	165	0.0325	0.0325	0.0325	0.0325	0.0325
Single Sons	110	0.0108	0.0295	0.0406	0.0086	0.0317
Married Daughters	238	0.0073	0.0062	0.0129	0.0047	0.0066
Married Sons	238	0.0075	0.0075	0.0109	0.0067	0.0081
Two Children Families						
Single Daughters	361	0.0153	0.0153	0.0153	0.0153	0.0153
Single Sons	238	0.0055	0.0176	0.0244	0.0043	0.0190
Married Daughters	675	0.0051	0.0044	0.0094	0.0033	0.0048
Married Sons	732	0.0030	0.0031	0.0046	0.0026	0.0033
Three Children Families						
Single Daughters	282	0.0106	0.0106	0.0106	0.0106	0.0106
Single Sons	226	0.0051	0.0163	0.0228	0.0040	0.0176
Married Daughters	631	0.0043	0.0037	0.0081	0.0028	0.0041
Sons w/ Spouse	686	0.0024	0.0024	0.0037	0.0021	0.0026
Four Children Families						
Single Daughters	205	0.0061	0.0061	0.0061	0.0061	0.0061
Single Sons	210	0.0031	0.0114	0.0161	0.0024	0.0123
Married Daughters	457	0.0037	0.0032	0.0069	0.0023	0.0035
Married Sons	432	0.0018	0.0019	0.0029	0.0016	0.0021
Five Children Families						
Single Daughters	99	0.0043	0.0043	0.0043	0.0043	0.0043
Single Sons	93	0.0034	0.0079	0.0104	0.0030	0.0086
Married Daughters	247	0.0020	0.0020	0.0034	0.0015	0.0021
Married Sons	261	0.0011	0.0010	0.0016	0.0010	0.0012

Notes:

1. Each element in the table is the Pr $[t > 0 \mid Gender, Effect]$.

2. The elements corresponding to single children use the Pr[that child provides care], and the elements corresponding to married children use the Pr[that child or the spouse of that child provides care].

Table 11

Decomposition of Child Gender Effects on $\frac{\Delta^2 \log \Pr[t>0]}{\Delta \text{Effect} \Delta \text{Male}}$

	All Effects	Just Wage Effect	Just Quality of Care Effect	Just Burden Effect
Single Children				
One Child Families	-1.080	-0.072	0.246	-1.306
Two Children Families	-1.245	-0.077	0.252	-1.474
Three Children Families	-1.244	-0.074	0.262	-1.489
Four Children Families	-1.384	-0.077	0.265	-1.627
Five Children Families	-0.917	-0.081	0.193	-1.051
Married Children				
One Child Families	-0.159	0.009	-0.356	0.170
Two Children Families	-0.157	0.020	-0.334	0.154
Three Children Families	-0.159	0.005	-0.337	0.160
Four Children Families	-0.173	-0.011	-0.324	0.148
Five Children Families	-0.040	-0.027	-0.160	0.173

Notes:

1. Each element in the table is the

$$\left(\log \Pr\left[t > 0 \mid Male, Effect\right] - \log \Pr\left[t > 0 \mid Female, Effect\right]\right)$$
$$- \left(\log \Pr\left[t > 0 \mid Male, No\ Effects\right] - \log \Pr\left[t > 0 \mid Female, No\ Effects\right]\right).$$

   These can be turned into percentage changes by exponentiating and subtracting one.

2. The elements corresponding to single children use the $\log \Pr$[that child provides care], and the elements corresponding to married children use the $\log \Pr$[that child or the spouse of that child provides care].

Table 12

Decomposition of Child Race Effects on $\frac{\Delta^2 \log \Pr[t>0]}{\Delta \text{Effect} \Delta \text{White}}$

	All Effects	Just Wage Effect	Just Quality of Care Effect	Just Burden Effect
Single Children				
One Child Families	-0.130	-0.043	0.106	-0.189
Two Children Families	-0.131	-0.045	0.109	-0.189
Three Children Families	-0.142	-0.048	0.112	-0.202
Four Children Families	-0.157	-0.049	0.114	-0.218
Five Children Families	-0.138	-0.050	0.113	-0.196
Married Children				
One Child Families	0.118	-0.042	0.248	-0.084
Two Children Families	0.123	-0.038	0.249	-0.083
Three Children Families	0.122	-0.039	0.251	-0.085
Four Children Families	0.124	-0.037	0.250	-0.086
Five Children Families	0.129	-0.036	0.256	-0.087

Notes:

1. Each element in the table represents

$$\begin{aligned}&(\log \Pr[t>0 \mid White, Effect] - \log \Pr[t>0 \mid Black, Effect]) \\ &-(\log \Pr[t>0 \mid White, No\ Effects] - \log \Pr[t>0 \mid Black, No\ Effects]).\end{aligned}$$

2. The elements corresponding to single children use the $\log \Pr$[that child provides care], and the elements corresponding to married children use the $\log \Pr$[that child or the spouse of that child provides care].

Table 13 χ^2 Goodness of Fit Tests						
Family Size	df	Mean Residual	χ^2 Statistic	Censored	# Censored Obs	Normalization
Time Help						
1	155	-0.02	$0.578*10^{18}$	457.70	66	17.19
2	737	0.00	80.81	80.81	0	-17.09
3	994	0.00	139.08	139.08	0	-19.17
4	605	0.01	$0.651*10^{6}$	1678.43	242	30.86
Financial Help						
1	308	1.03	$0.773*10^{6}$	194.17	21	-4.59
2	285	0.75	$0.166*10^{7}$	222.69	28	-2.61
3	350	0.14	$0.336*10^{7}$	176.01	19	-6.58
4	220	0.07	$0.557*10^{6}$	84.25	11	-6.47
Leisure						
2	744	-0.01	197.75	190.16	3	-14.36
3	994	0.07	447.65	447.65	0	-12.25
4	605	0.11	780.03	777.68	2	4.96

Notes:

1. A family of size M has $M-1$ children.

2. The statistics reported in the column labeled "Normalization" are normalized by subtracting off the mean of the censored χ^2_{df}, $0.978 \cdot df$, and dividing by the standard deviation, $\sqrt{1.722df}$. The relevant general formula is

$$
\begin{aligned}
E\chi^2_{1c} &= F_3(c) + c\left[1 - F_1(c)\right]; \\
E\left(\chi^2_{1c}\right)^2 &= 3F_5(c) + c^2\left[1 - F_1(c)\right]
\end{aligned}
$$

where χ^2_{1c} is a χ^2 random variable with one degree of freedom censored at c and $F_{df}(c)$ is the χ^2 distribution function with df degrees of freedom evaluated at c.

Table 14
Policy Experiments

		Number of Children			
	Expmnt #	0	1	2	3
Increase in formal care per \$q "formal care stamps"	1	0.48	0.35	0.34	0.33
Increase in informal care by children per \$ informal care subsidy for children	2	–	0.99	2.09	2.91
Increase in formal care per \$ increase in Medicaid Income limit	5	–	0.15	0.23	0.27
Increase in formal care per \$q "formal care stamps" conditional on ADLs	6	–	0.43	0.17	0.24

Note: All numbers are measured in hours.

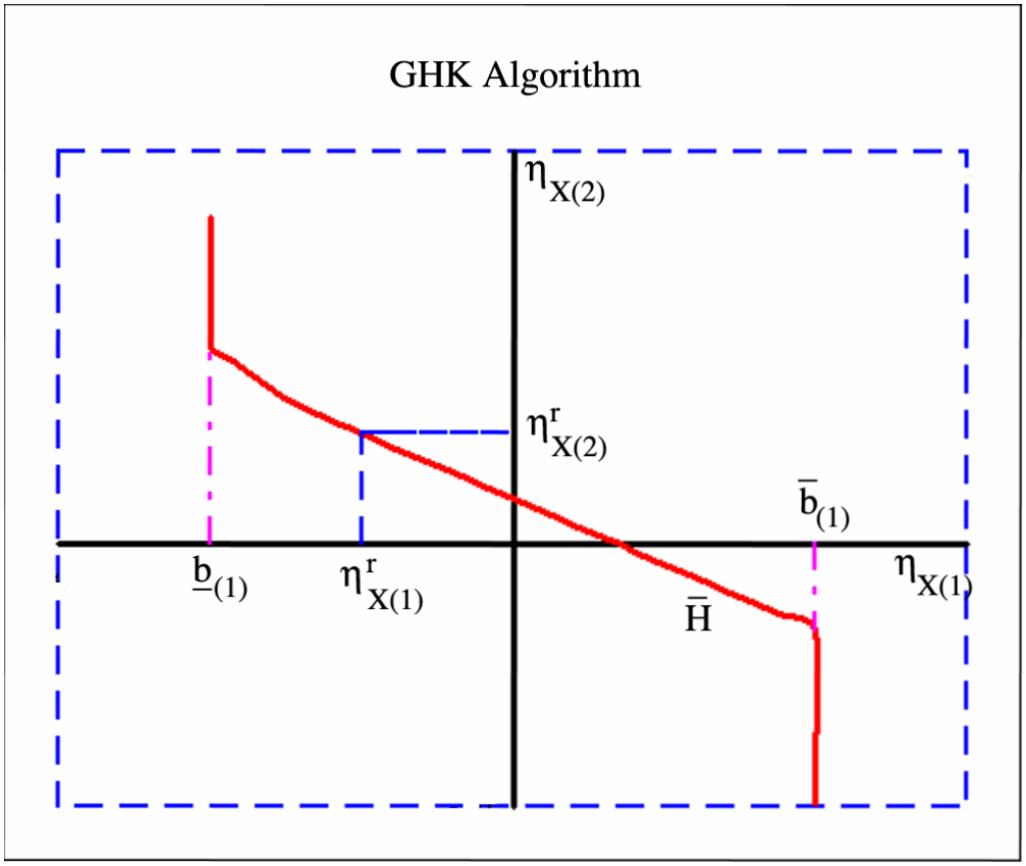

Figure 1:

Figure 1

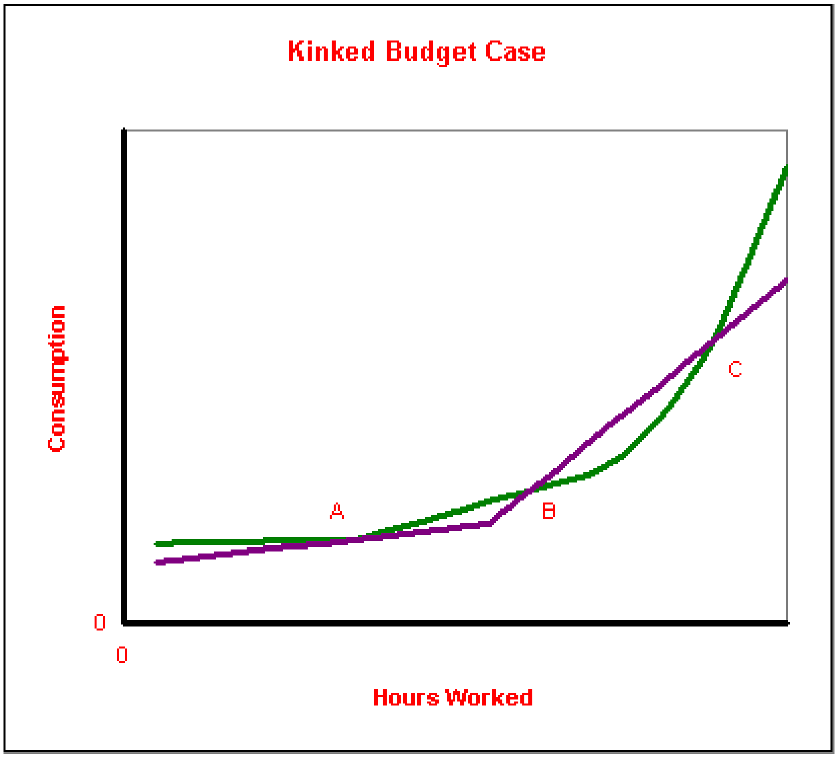

Figure 2:

Figure 2