1. Introduction

Over the last generation, there has been a marked shift: children are less likely to care for an elderly parent and elderly parents are more likely to live alone longer and are more likely to live in an institution such as a nursing home.[1] There are significant social and financial implications associated with this trend. Thus, it is worthwhile trying to understand how family decisions are made concerning care for an elderly parent.

While there is little work on this subject in the economics literature,[2] sociologists and social workers have extensively examined what factors affect family care decisions.[3] The typical primary caregiver, other than a spouse, is an oldest daughter, single, out of the labor force, and living with the parent or nearby. The more problems the parent has with activities of daily living (ADL) or instrumental activities of daily living (IADL), the more likely he or she will receive care.

The goal of this paper is to develop a game-theoretic model of family bargaining applied to the issue of long-term care. This has value in that developing methods to estimate such models will prove useful in the future. Furthermore, this paper sheds light on the extent to which existing data can be used to estimate family decision-making processes. Finally, the empirical results help us understand long-term care behavior.

We present two structural models of family decision making, one collective (in the sense that the entire family participates in the decision) and one voluntary (in which family members can refrain from participation), and then use data from the National Long-Term Care Survey to estimate the parameters of and test both models. The results provide some support for each model specification

[1] See, for example, Boersch-Supan, et al. (1988) or Wolf and Soldo (1988).
[2] Exceptions are Boersch-Supan, et al. (1988), Kotlikoff and Morris (1988), and Cutler and Sheiner (1993).
[3] See Horowitz (1985) for a good survey.

and slightly favor the voluntary model over the collective model. Then we use the parameter estimates of the voluntary model to simulate the effects of policy and demographic changes on family behavior. We explain the sign but not the magnitude of the existing long term trends in terms of the usual, empirically untested, explanations for them. Finally, we simulate the effects of alternative family bargaining rules on individual utility to measure the sensitivity of our results to the family decision-making assumptions we make.

2. The Model

Consider a family with N children where children are indexed by their birth order with the oldest first. The parent or parents are treated together as one individual, indexed by zero. We examine the issue of which family member becomes the primary caregiver, or whether the parent moves to a nursing home, or remains alone with no care provided by the children.

The payoff to family member i will be expressed as the sum of (up to) three terms. The first term V_{ij} represents the value to i of care choice j. Cox (1987), Browning et al. (1994), and Bernheim, Schleifer, and Summers (1985), consider alternative models of family decision making where each family member potentially includes the value of other family members in her own utility function. Our V_{ij} matrix can allow for this type of interdependence. The second term represents the net side payments made or received by i, if any. The third term is present if i participates in the care decision and represents the direct net benefit of participation. We now explain each of the terms in further detail.

Let V_{ij} denote the value to i (the ith child if $i > 0$, the parent if $i = 0$) of the care option j. Care option j for $j > 0$ means that child j is the primary caregiver; for $j = 0$, it means that the parent lives alone with no care provided; and for $j = -1$, it means that the parent lives in a nursing home. The matrix V_{ij} is normalized by setting $V_{i0} = 0$ for all i.[4] Thus V_{ij} can be interpreted as the increment to i's utility from care option j relative to the parent receiving no care. We model V_{ij} as depending on characteristics of the parent, of the children i and j for $j > 0$, and of nursing homes for $j = -1$. Some of these characteristics are observed by the econometrician, and some are not. We assume that the entire matrix V_{ij} is known to all family members.

Throughout this section we consider two examples to aid in the discussion.

Example 1: Consider a family with two children in which the V matrix takes the form

$$V = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 4 & -1 \\ 0 & -1 & 4 \end{bmatrix}. \tag{2.1}$$

Recall that rows indicate family member $i = 0, 1, 2$ and columns indicate care option $j = 0, 1, 2$ (no nursing home option is available). In this example the parent is indifferent among all three care options. Each child prefers to take care of the parent herself rather than have the parent receive no care, but care by the sibling is regarded as the worst outcome.

Example 2: Consider a family with two children in which the V matrix takes the form

$$V = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 2 & 4 \\ 0 & 4 & 2 \end{bmatrix}. \tag{2.2}$$

Now each child prefers that the other provide care.

In general, we allow for side payments to be made between family members.[5] In principle, any family member could make a side payment (possibly negative) to any other. But to keep things simple, and without restricting the possible patterns of transfers among family members, we confine

[4] A different normalization is more convenient for the empirical work.

[5] Heideman and Stern (1996) consider an alternative model of long-term care decision making where side payments are not allowed.

the side payments to those made by a child to the parent. Let s_i denote the net side payment made by child i to the parent. A $s_i < 0$ is interpreted as a payment of size $-s_i$ from the parent to the child. The utility of all family members is linear and additive in the parent care term and the side payment term. Thus, if j is chosen to care for the parent and child i's side payment is s_i, then the increment to i's utility is

$$U_i = V_{ij} - s_i. \tag{2.3}$$

The utility of the parent is

$$U_0 = V_{0j} + \sum s_i, \tag{2.4}$$

where the sum is over all children making or receiving the payments.

2.1. The Parental Care Decision

We present two different ways to model the family decision about caring for the parent. First, the collective model assumes that the entire family participates in a once-and-for-all decision and chooses the care alternative that maximizes the sum of everyone's payoff (i.e., chooses j to maximize $\sum_{i=0}^{N} V_{ij}$). The benefits are divided according to a well specified benefit-sharing rule. Various rules are discussed below.[6]

In the collective model, it can turn out that there are some children who would, if they could, choose not to participate in the decision (consider example (2)). One can avoid this problem by building a voluntary model. Given the benefit-sharing rule, each child decides independently whether to participate without knowing the participation decisions of the other children.

[6] In examples (1) and (2), there is a tie between care by either child. We can assume a tie-breaking rule such as child 1 provides care in case of a tie. Alternatively, we can assume V_{11} is actually ϵ higher than stated in the examples where ϵ is a small positive number.

Various benefit-sharing rules for the voluntary model are considered: ex-ante Pareto-efficient rules as well as two sharing rules that appear in the literature but that are not ex-ante Pareto-efficient in this model. The two efficient rules considered are the one that maximizes the parent's expected utility and the one that maximizes the sum of all family members' expected utilities. The two other ways of dividing the benefits are a) using the Shapley value and b) splitting the rents equally. Benefit-sharing rules are not relevant to the collective model.

The voluntary model of the family decision about caring for the parent can be interpreted as follows. First it is agreed that all of those who wish to do so can attend a meeting at which the issue is to be decided.[7] Those present at the meeting either choose (from among those present) the child who is to be the primary caregiver, decide that the parent should move to a nursing home, or decide that the parent should receive no care. Side payments can be made among those present. Those not present have to accept the decision of those who are, but they can not be chosen to be the primary caregiver, and they neither receive nor are required to make any side payments.

The decision at the meeting is determined as follows. Suppose that the subset M is present, and that $0 \in M$, i.e., the parent attends. (Our assumptions ensure that it is never in the parent's interest to be absent from the meeting.) The primary caregiver is chosen to be $j^*(M)$ such that, among all care options j available to those present, $j^*(M)$ makes the sum $\sum V_{ij}$ as large as possible where the sum is taken over all i who are present:

$$j^*(M) = \underset{j \in M \cup \{-1\}}{\operatorname{argmax}} \sum_{i \in M} V_{ij}. \tag{2.5}$$

The reason those present make this choice is that, if they were to choose a feasible j that did not

[7] It is not necessary that an actual meeting take place. What is needed is that each child decides whether to participate in the care decision without observing the decisions of the other children.

maximize this sum, then choosing $j^*(M)$ instead would allow them all to increase their utilities because side payments can be made.[8]

If $j^*(M) = 0$ is chosen, no care is provided because $\sum_{i \in M} V_{ij} \leq 0$ for all $j \in M \cup \{-1\}$. (Recall that $V_{i0} = 0$ for all i.) If $j^*(M) > 0$ is chosen, child $j^*(M)$ is the primary caregiver. If $j^*(M) = -1$ is chosen, the parent is transferred to a nursing home. For simplicity let V_M^i denote $V_{ij*(M)}$, i's utility term when the set M show up for the meeting.

Reconsider example (1) and assume that an "equal rent splitting rule" is used: if the subset M attends the meeting, the surplus accruing to those present over what they would get if the parent receives no care V_M is equally divided among the $|M|$ people present, so that each receives a utility increment of $V_M / |M|$. Then the payoff matrix of the game representing the participation decisions of the children is

Child 1

	N	P
N	$0, 0$	$-1, 2$
P	$2, -1$	$1, 1$

(2.6)

where P indicates "participate" and N indicates "not participate." This game has a Nash equilibrium in strictly dominant strategies: whatever the other child does, each child does better by participating in the decision.

In example 2, the payoff matrix is

Child 2

Child 1

	N	P
N	$0, 0$	$4, 1$
P	$1, 4$	$2, 2$

. (2.7)

Now the best choice for each child depends on what the other child is expected to choose. There are three Nash equilibria: two having just one child participate, and the other in mixed strategies

[8] In general, we assume that, no matter which set M attends the meeting, there is a unique $j^*(M)$ maximizing this sum. If the values V_{ij} are random, have a continuous distribution, and the covariance matrix is of full rank, then there is zero probability of a tie in the contest to maximize the sum above.

with each child expected to participate with probability 1/3.

As example 2 illustrates, it is possible that multiple equilibria exist and equilibria with random behavior (i.e. mixed strategies) can arise easily. It is also possible to construct examples for which no pure strategy equilibrium exists. A common way to adapt a model so that deliberate randomization is not necessary is to introduce a small amount of private information. Private information enters into this model via a third and final term in the payoff to child i. If i participates in the decision, the final term is e_i so i's payoff is $V_{ij} - s_i + e_i$; otherwise the final term is zero so the payoff is as in equation (2.3).[9] Assume that only player i knows the magnitude of e_i, but its distribution F_i is common knowledge, and it is common knowledge that the e_i are independent. Suppose that, for example, F_i has a normal distribution or any other distribution with support the real line. Then, as viewed by others, there is some positive probability p_i that player i attends the meeting (which occurs if e_i is a large enough positive number), and a positive probability $1-p_i$ that i will be absent (which occurs if e_i is a large enough negative number).[10]

Once we introduce the e_i terms representing each child's privately-known value of participating in the decision, we obtain a probability between zero and one of participating. In example 1, Child i will choose to participate as long as $e_i > -2$. Suppose that $F_i(-2) = .2$, so that each child participates with probability .8. Then the probability distribution over all subsets S of $M = \{1, 2\}$, the set of children, puts a probability of .64 on $\{1, 2\}$ (both children participate), a probability of .04

[9] We first considered introducing a private information term into V_{ij} but doing so made it much harder for us to solve the family's decision problem, and the error term did not help us obtain a unique pure strategy equilibrium.

[10] A different approach that leads to similar results is to suppress the private information term e_i and then to look for an equilibrium in the game in which each child decides whether to attend or not, for a given side payment rule. A Nash equilibrium always exists but it may involve mixed strategies, and so the children are unsure about which of their siblings participate. The equilibrium strategies determine a distribution over the set of those who attend, and the analysis corresponds closely to the case considered in the text. This parallel between mixed strategy equilibria in games of complete information and pure strategy equilibria in games with private information was first pointed out by Harsanyi (1973).

on (neither child participates), and a probability of .16 on $\{1\}$, the event that child 1 participates but 2 does not, and .16 on $\{2\}$, the reverse. Since the parent always is assumed to participate, in the same way we derive a distribution over the subsets of $A = \{0, 1, 2\}$ of all family members who participate. Now the set A has probability .64, $\{0\}$ has probability .04, and $\{0, 1\}$ and $\{0, 2\}$ each have probability .16.

If the equal rent splitting rule is used in example 1, the parent nets zero if neither child participates, 2 if just one child participates, and 1 if both children participate. Thus the parent's expected payoff is

$$E\left[V_M / |M|\right] = .04\,(0) + .32\,(2) + .64\,(1) = 1.28. \tag{2.8}$$

In general, the probability vector (p_i) determines a probability distribution over the subsets S of family attending the meeting, where

$$\text{Prob}\,(S) = \prod_{i \in S} p_i \prod_{i \notin S} (1 - p_i) \tag{2.9}$$

for all $S \subset A$, the set of all family members. The operator E denotes expectation with respect to this distribution. Each child considers the distribution of the subset of others attending the meeting. Some extra notation helps describe the situation facing a child (j say) and her beliefs about the subsets of the rest of the family, $A \backslash \{j\}$, who might attend the meeting. For any subset M of family members (e.g., $M = A \backslash \{j\}$), the values p_i for $i \in M$ determine a probability distribution over subsets S of M who attend the meeting, where

$$\text{Prob}\,(S) = \prod_{i \in S} p_i \prod_{i \in M \backslash S} (1 - p_i)\,, \tag{2.10}$$

for all subsets S of M. We use the operator E_M to denote expectation with respect to the distribution of subsets of M. For brevity we will denote $E_{A\backslash\{j\}}$ by E_j and $E_{A\backslash\{i,j\}}$ by E_{ij}.

In example 1 with the equal splitting rule and $F_i(-2) = .2$, child 1's expected payoff if 1 participates is

$$E_1\left[V_{M\cup\{1\}}/\left|M\cup\{1\}\right|\right] = .2\,(2) + .8\,(1) = 1.2.$$

2.2. Determining the Probabilities p_i and Other Equilibrium Issues

For each child i, the decision whether to attend the meeting depends on the size of the e_i term, the side payments that i anticipates, and the effect that i's presence at the meeting would have on $j^*(M)$ for each M. Because we assume that everyone is risk neutral and that the e_j terms are independent, the only aspect of the side payments that is relevant to i is the expected amount of side payments made by i if i attends the meeting. Let m_i denote this conditional expected side payment. Player i expects to do better by attending than not attending if and only if

$$e_i - m_i + E_i V^i_{S\cup\{i\}} > E_i V^i_S \tag{2.11}$$

or

$$e_i - m_i + \Delta_i V^i > 0 \tag{2.12}$$

where $\Delta_i V^j$denotes $E_i\left[V^j_{S\cup\{i\}} - V^j_S\right]$, the expected change in the value to j of parental care arrangements if i attends. In example (1), $\Delta_1 V^1 = .2\,(4-0) + .8\,(4-(-1)) = .48$. The threshold level of e_i at which i would be indifferent between attending or not is given by

$$t_i = m_i - \Delta_i V^i, \tag{2.13}$$

and the probability of i attending (as viewed by everyone other than i) is

$$p_i = 1 - F_i\left(t_i\right).^{11} \tag{2.14}$$

To see that there is always a solution to equations (2.13) and (2.14) for all expected side payments, note that they reduce to

$$p_i = 1 - F_i\left(m_i - \Delta_i V^i\right). \tag{2.15}$$

As long as m_i is a continuous function of the set of p_i's, the right hand side is a continuous function of the vector (p_i) and lies between zero and one, so that the Brouwer fixed point theorem ensures that a solution exists. All sidepayment rules considered in this paper satisfy the continuity condition.

Both the voluntary and collective model fit in this framework. The voluntary model corresponds to $Ee_i = 0$. On average, children have no extra incentive to participate in the decision about parental care and act strategically. The collective model lets $Ee_i \to \infty$. As $Ee_i \to \infty$, $p_i \to 1$ and each family member commits to sharing in the decision.

In the voluntary model (as in the collective one) we assume that all participants agree to abide by the joint decision. This rules out the possibility that a participant, finding the resulting decision very onerous, refuses to accept it. In cases like this we can not conclude that the participant would do better to refuse rather than accept the decision because the model does not pin down the consequences of such a refusal. One might assume that all the remaining participants make the

[11] It is here that the assumption that the family decision is made once only is used. In particular, if the family were to make repeated decisions, each family member i would consider the information revealed to other family members about her e_i by her actions in early rounds and how that information would affect her expected utility in later rounds.

same decision as they would have had the other participant never agreed to take part. However, since we already are allowing one of the original participants to renege, it would seem artificial to forbid other participants from following suit if they wished to do so. The result of this possible chain of refusals is unpredictable. In the extreme case all participants might withdraw so that the parent would receive no care. For reasonable side-payment rules like the equal rent-splitting rule that we use, each participant does at least as well abiding by the decision as she would if the decision-making mechanism were to collapse and no care were to be provided.

Ensuring the existence of an equilibrium is handled with different methods in other empirical equilibrium models. Bresnahan and Reiss (1990) show that simultaneous move games can be written as a set of simultaneous equations with dummy endogenous variables as in Heckman (1978). Such a model is logically consistent only under restrictive assumptions about the coefficients on the dummy endogenous variables. Logical inconsistency in Heckman (1978) is equivalent to a lack of equilibrium/multiplicity of equilibria in Bresnahan and Reiss (1990). Bresnahan and Reiss suggest solving the problem by restricting the support of the random errors in the model to avoid existence and multiplicity problems. Berry (1992) ensures the existence of an equilibrium in a model of entry by assuming that the value of participating in the market decreases with the number of entrants and that the value of not participating is zero. The first assumption is equivalent to following the suggestion of Bresnahan and Reiss (1990). While Berry's solution is reasonable in an entry model, it is not appealing for our model of family decision making. The empirical auction literature (see, for example, Laffont and Vuong 1993 or Paarsch 1992) assumes a distribution of unobserved heterogeneity and then computes the distribution of the winning bid. The role of unobserved heterogeneity plays a significantly different role in such models compared with our participation error. Heidemann (1992) describes dual retirement decisions in a family as a Stackelberg game to avoid the equilibrium existence problems associated with simultaneous move games.

2.3. Pareto Efficient Side Payments

The class of ex-ante Pareto-efficient rules can be found by solving an equivalent class of social planner's problems: choose side payment rules to maximize the weighted sum of all family members' expected utilities where the weights w_i are nonnegative and not all zero. See Appendix A for the derivation.

We concentrate on two special cases:

1. The arrangements are designed to maximize the sum of all family members' expected payoffs, so that $w_0 = w_1 = \ldots = w_N = 1$. Equation (A.13) reduces to

$$\sum_{j \geq 0} \Delta_i V^j + t_i = 0 \text{ for all } i. \tag{2.16}$$

The meaning of this condition is that child i should participate in the decision if and only if the extra utility obtained from participating plus the sum of everyone's expected gains from including i amongst the potential care givers is positive.

2. The parent designs the arrangements and does so in order to maximize the parent's expected utility. Then $w_0 = 1$, but $w_i = 0$, for all $i > 0$. Equation(A.13) reduces to

$$\Delta_i V^0 + \Delta_i V^i - p_i / f_i\left(t_i\right) + t_i + \sum_{\substack{j>0 \\ j \neq i}} p_j \Delta_{ij} V^j = 0. \tag{2.17}$$

The meaning of this is made clearer by using equation (2.13) to rewrite equation (2.17) as

$$\Delta_i V_0 + m_i - \frac{p_i}{f_i(t_i)} + \sum_{\substack{j>0 \\ j\neq i}} p_j \Delta_{ij} V^j = 0. \tag{2.18}$$

The left hand side represents the marginal benefit to the parent of raising the probability of i's participation (by reducing i's expected side payment). The first term is the direct effect on the parent's valuation of the care arrangement; the second represents the greater likelihood of receiving the side payment; the third term represents the expected cost of lowering the side payment required of i; while the final sum represents the effect of i's more probable participation on other children's expected gains from participating which is appropriated by the parent as increased expected side payments from them.

One could model bequests in a way similar to Bernheim, Shleifer, and Summers (1985) using a slight extension of this model. Suppose the parent gets utility from granting bequests to her children. Assume, as in the game described in Bernheim, Shleifer, and Summers (1985), that the parent's decision rule has two parts: first choose a total amount B to bequeath, and then choose an allocation rule. The total bequest B depends upon a tradeoff between the utility the parent gets from her children's utility and the utility she gets from her own consumption. The allocation rule depends upon the children's actions (whether to participate in the care decision). Then the parent's problem is to choose a side payment $s_i(M)$ for all i and M that depends upon the subset M of family members who participate such that $s_i(M) \leq 0$ if $i \notin M$ and $\sum_i s_i(M) = -B$. The first restriction says the parent can do nothing worse to a child than disinherit him unless the child participates. The second restriction follows from the assumption of a two step game. The parent chooses a side-payment rule that maximizes her own welfare subject to the restrictions. The solution to such a problem is discussed in Appendix D. Its solution is difficult to compute, and thus this side-payment rule is not pursued further.

2.4. Shapley Side-Payment Rules

A division rule widely used in cooperative game theory is the Shapley value. The Shapley value is the only rule that satisfies four requirements: symmetry, efficiency, linearity, and that noncontributors receive no benefit. These four requirements are stated more fully in Appendix B.

More concretely, if the subset M attends the meeting, the Shapley Value accruing to participant i is the weighted sum:

$$\pi_M(i) = \sum_{S \subset M \backslash \{i\}} q(|S|) \left(V_{S \cup \{i\}} - V_S \right) \tag{2.19}$$

where $q(|S|) = |S|!(|M| - |S| - 1)!/|M|!$, and $|S|$ is the number of elements in S.

The sum in equation (2.19) is the expected marginal contribution made by i in the following sense. Suppose that the $|M|$ participants line up outside a room in random order, with all orderings being equally likely, each having probability $1/|M|!$. The participants then file into the room and each receives her marginal contribution, i.e., the increment that she adds to the value of the coalition in the room. For any set S not containing i, there are $|S|!(|M| - |S| - 1)!$ permutations such that S is the set of those who precede i in line. Thus $q(|S|)$ is the probability that S is the set of predecessors of i. Hence the Shapley Value is the expected payoff received by i.

3. The Data

The data consist of a sample of 1952 families drawn from the National Long-Term Care Survey. Elderly people who passed a series of screening questions[12] were surveyed in 1982 about their living arrangements and were reinterviewed in 1984. There is some demographic information about them and each of their living children. We use the 1984 data to estimate the model and the 1982 data to construct instruments. The sample is restricted to families with 5 or fewer children for computational reasons. Only families in which the parent lived alone in 1982 are included (for econometric reasons discussed in Section 4).

The parents in the sample are predominantly white and female. The average age of parents is 77.3, and almost half are still married. Most have some problem with an activity of daily living (ADL).[13] The children are, on average, in their middle 40's, married, and work. There is a wide distribution of distances between the parent and children.

The dependent variable is the care provision for the parent. The parent is asked to list children (either at home or away from home) and whether each provides help. If only one child is listed as providing significant help, that child is designated the primary caregiver. If more than one child is listed, the one providing the most hours is designated the primary caregiver.[14] If no child is listed, then the parent is designated as "living alone." If the parent lives in a nursing home, then the

[12]The screening questions were used to oversample people with health conditions likely to cause someone to need long-term care. They were mostly questions about the parent's health and ADL's and are exogenous with respect to the dependent variables in this analysis. The other sampling procedure details are not relevant for this analysis but are available in Macken (1986). There is another wave of NLTCS in 1989 not used in this paper.

[13]ADL's include problems with eating, dressing, bathing, using the toilet, getting out of bed, and walking indoors.

[14]In our sample, among those families (with at least two children) with some care provision by children, the proportion of families with just one care provider ranges from 55% in families with five children to 76% in families with two children. In the same subsample, at least 75% of care hours are provided by one child in 70% of families with five children, and this rises to 85% of families with two children. In the same subsample, less than 80% of care is provided by one child in 14% of the families.

nursing home is the primary caregiver.[15]

In this sample, most of the parents live alone, and living in a nursing home is the least common choice. The proportion of parents receiving help from a child is much lower than in other work such as Wolf and Soldo (1991) for three reasons: we include married as well as unmarried parents, we include people in nursing homes, and everyone in this sample lived alone two years previously.

There are three policy variables used which vary by state of residence of the parent in the estimation program. The first, PROGRAM, indicates whether a "medically needy" program exists in the state; i.e., it indicates whether the parent is able to deduct medical costs from income in determining eligibility for Medicaid. Medically needy programs allow middle-class parents to have Medicaid pay for nursing home costs. The second and third variables, RESLIM and INCLIM respectively, are the state's resource (asset) limit and income limit for Medicaid eligibility. These variables are described in more detail in, for example, Cutler and Sheiner (1993).

There are a number of problems with the data set which are discussed in detail in Stern (1995). These include:

a) The number of grandchildren in 1984 is severely underreported. We use 1982 grandchildren as a proxy for 1984 grandchildren.

b) The number of children alive in 1984 is too small relative to the number alive in 1982.

c) The income variable is noisy and missing for too many observations and thus is not used.

d) Many families have nonsensical variable values that need to be corrected with reasonable imputation rules. For example, if the data indicate that the parent changes gender between 1982 and 1984, the spouse's gender is used to infer the correct gender. Also, significant imputation is

[15]We do not distinguish among other types of caregiving such as paid help, care from a sibling, etc. because a) there are not enough observations for each of these types of help and b) the characteristics of these alternatives are not observed when they are not chosen.

necessary to make sense of children's gender and age between 1982 and 1984.

Nevertheless, these are, by far, the best data for this analysis presently available in that this is the only representative sample of any size with sufficient information on each family member at least for two years. More details on the National Long-Term Care Survey are available in Macken (1986). A fruitful source of data for future work is the new Health and Retirement Survey. See Soldo and Hill (1996) for details about the relevant information.

4. Estimation Procedure

4.1. Specification

The first step in estimating the model described in Section 2 is to specify parts of the model further. In particular, we let the value of alternative j to family member i be

$$V_{ij} = X_0\beta_j + X_j\psi + X_j\gamma\delta_{ij} + Q_{ij}\alpha + u_{ij} \tag{4.1}$$

where X_0 includes characteristics of the parent, X_j includes characteristics of the jth alternative, and Q_{ij} includes differences in characteristics between member i and alternative j. For example, X_0 includes the age, race, gender, education, and ADL indicators of the parent. One might expect, for example, that V_{i0}, the value to i of the parent living alone, decreases with the presence of each ADL. The X_j characteristics include, for example, the distance of j from the parent, j's gender, marital status, and work status. Child j's value as a caregiver should decline if she lives far away or has other significant responsibilities such as work or a spouse. The X_j characteristics affect V_{ij} in that i cares about the quality of care j can provide (measured in $X_j\psi$). But if $i = j$, then X_j affects V_{ij} also in that X_j may affect the burden associated with providing care (measured in $X_j\gamma\delta_{ij}$) where δ_{ij}

(the Kronecker delta) is equal to 1 if $i = j$ and zero otherwise.[16] The Q_{ij} variables are proxies for the relationship between children i and j.[17] They might include the distance between the children or differences in gender, age, or marital status. For example, if children i and j live close to each other, they may value each other as care providers because each can visit the other and/or monitor the other easily. Intuition does not predict how differences in gender, age, or marital status should affect V_{ij}. Browning, et al. (1994) might interpret our $X_j \gamma \delta_{ij}$ effect as the direct effect of these characteristics on utility and the $X_j \psi$ as the indirect effect through other family member's utility functions. The $Q_{ij} \alpha$ terms would have a similar interpretation.

The error associated with equation (4.1) u_{ij} measures unobserved components of V_{ij}. We assume a degenerate distribution of u_{ij} in our empirical work, but we could allow for a nondegenerate distribution by using the method of simulated moments (McFadden 1989 or Pakes and Pollard 1989). In particular, this involves only simulating the integral of the residuals described below over the distribution of the u's.

Next, we specify the value of participating in family meetings, e_i, as

$$e_i \sim \text{ iid } N\left(\mu, \sigma_e^2\right) \tag{4.2}$$

where $\mu = 0$ for the voluntary model and $\mu \to \infty$ for the collective model. Technically, μ is identified by the data. However, we choose to specify its value and then estimate the remaining parameters conditional on μ. Finally, the equal rent-splitting rule is used to determine side payments.

[16] The X_j variable in the second term of equation (4.1) when $j = 0$ is defined to equal zero because parent characteristics are captured in $X_0 \beta_j$. The X_j variable in the third term of equation (4.1) when $j = -1$ (nursing home) is irrelevant because $\delta_{ij} = 0$ when $j = -1$ for all i.

[17] Q_{ij} is equal to zero if either $i < 1$ or $j < 1$.

4.2. Estimation

The specification of the V_{ij}'s in equation (4.1), the normal distributional assumption in equation (4.2), and the equal rent-splitting rule[18] can be used to determine equilibrium p's.[19] The details of this are discussed in Appendix C.

Each family is treated as an equilibrium observation, and only a small part of equilibrium behavior is observed. This is similar to the assumption made about families in Heidemann (1992) or city pairs in Berry (1992). If we observed which family members participated in the family decision, our data would be structurally equivalent to Berry's. In fact, we observe only the outcome of the family decision (which depends upon the subset of the family deciding). Our data are quite different from those in papers such as Eckstein and Wolpin (1990), Olley and Pakes (1991), and Berry, Levinsohn, and Pakes (1995) in which a small number of equilibria are observed (at most one per year in a short panel) but much detail is observed per agent.

Once equilibrium p_i's are determined, we can derive $\text{Prob}\,(K)$ in equation (2.9) for each family subset K. Conditional on K, equation (2.5) determines the best choice, $j^*(K)$. Thus, we can compute the probability that the jth alternative is chosen by adding up probabilities of family subsets K where $j^*(K) = j$:

$$\text{Prob}\,[j \text{ chosen}] = \sum_{K \subset A} \delta_{jj*(K)}\, \text{Prob}\,[K] \tag{4.3}$$

for all possible alternatives j where $\delta_{jj*(K)} = 1$ if $j = j^*(K)$ and 0 otherwise.

The dependent variable for family n can be thought of as a vector Y_n where $Y_{nj} = 1$ if j is

[18] Recall that m_i is the expected sidepayment made by i conditional on participating. This is easily calculated using the equal rent-splitting rule.

[19] Note that $p_i \to 1$ in the collective model.

the chosen care alternative and $Y_{nj} = 0$ otherwise. Then $EY_{nj} = \text{Prob}\,[j \text{ chosen}]$ in equation (4.3). Let $y_n = Y_n - EY_n$ be the vector of residuals for family n, and let y be the residuals stacked by family. Let Z be a matrix of instruments, described in Stern (1995), that are needed because some child characteristics, in particular distance and work status, may be endogenous. Let the vector of parameters be $\theta = (\beta, \psi, \gamma, \alpha, \sigma_e)$. Then the instrumental variables estimator of θ is

$$\hat{\theta} = \underset{\theta}{\text{argmin}}\ \ y'ZZ'y. \tag{4.4}$$

In fact, given equation (4.3), for some θ, $\text{Prob}\,[j \text{ chosen}] = 0$ or $\partial\,\text{Prob}\,[j \text{ chosen}]\,/\partial\theta$ does not exist. This is problematic, especially when estimators relying on instruments that are proportional to the reciprocal of $\text{Prob}\,[j \text{ chosen}]$ are used or when derivatives are needed. In order to smooth equation (4.3), following Horowitz (1992) and McFadden (1989, 1991), we append an extreme value error with a small variance to $\sum_{i \in M} V_{ij}$ in equation (2.5):

$$j^*\,(M) = \underset{j \in A \cup \{-1\}}{\text{argmax}} \left[\sum_{i \in M} V_{ij} + \eta\epsilon_j\right] \tag{4.5}$$

where $\epsilon_j \sim$ iid Extreme Value. Define $V_{Mj} = \sum_{i \in M} V_{ij}$ if $j \in M$ and $V_{Mj} = -\mathfrak{B}$ if $j \notin M$ where $\mathfrak{B}$ is sufficiently large. Then equation (4.3) becomes

$$\Pr\,[j \text{ chosen}] = \sum_{M \subset A} \text{Prob}\,[M]\, \frac{\exp\{V_{Mj}/\eta\}}{\sum_{k \in A \cup \{-1\}} \exp\{V_{Mk}/\eta\}} \tag{4.6}$$

which is differentiable almost everywhere and always positive.[20]

If there were no potential endogeneity problems, then the instruments would be $\partial \log EY_n/\partial\theta$.

[20] In the application, we set $\mathfrak{B}$ equal to 1 and $\eta = 0.25$.

However, work status and distance of the child may be endogenous; the chosen caregiver may choose not to work or to move closer to the parent to provide better care.[21] We control for endogeneity by using the 1982 work status and distance in evaluating $\partial \log EY_n / \partial\theta$. People living alone in 1982 were very likely to live alone in all relevant years prior to 1982 (see Stern, 1995). Since we limit the sample to parents who live alone in 1982, there is no variation in the dependent variable in 1982 or any relevant year prior to it. Thus, instruments can not be correlated with the lagged dependent variable. Conditioning on the parent living alone in 1982 alters the distribution of any unobservables in 1984. However, in a similar model, Stern (1994) shows that, though theoretically relevant, the problem is empirically unimportant in terms of coefficient estimates or their standard errors. A second order expansion of EY_n shows that the instruments will be correlated with the residuals used in equation (4.4) because EY_n is a nonlinear function of the endogenous regressors.[22] We performed a Monte Carlo study to measure the size of the bias caused by this problem. For this application, the simulated biases are very small and statistically insignificant because the instruments are very good predictors of the endogenous regressors.

The asymptotic covariance matrix of $\hat{\theta}$ is

$$\text{plim} \left[\frac{Z' y_\theta}{\mathfrak{N}}\right]^{-1} \left[\frac{Z' y y' Z}{\mathfrak{N}}\right] \left[\frac{y_\theta' Z}{\mathfrak{N}}\right]^{-1} \tag{4.7}$$

where $y_\theta = \partial y / \partial\theta$ and $\mathfrak{N}$ is the sample size. However y_θ does not exist at many points and, in general, is a poor indicator of properties of $\hat{\theta}$ outside of a small neighborhood of the true value of

[21] If any of the X_{ij}'s are really endogenous, one should model their determination simultaneously with care provision. This was done in a somewhat different model in Stern (1994, 1996). Unfortunately the data has very little information about variables that would affect the work and location decisions. Also, the modeling procedure becomes significantly more difficult. Our approach is a compromise between trying to model these decisions simultaneously and just ignoring potenetial endogeneity.

[22] We thank Tom Mroz for patiently explaining this to us.

θ.

As an alternative, we use a bootstrap-like estimator of the covariance matrix. Given $\hat{\theta}$ we simulate R samples of data[23] and then estimate θ for each simulated sample. The distribution of the estimates from the simulated samples is used to construct estimates of the variances of our estimators. Since estimation is computer intensive, we choose $R = 40$.

4.3. Identification

In order to verify the identification of the parameters, β, ψ, δ, and α, in equation (4.1), consider the collective model in which everyone always takes part in the care decision. Then the probability of alternative j being chosen is multinomial logit (assuming $\eta > 0$) with deterministic terms

$$\sum_i V_{ij} = NX_0\beta_j + NX_j\psi + X_j\gamma + \sum_i Q_{ij}\alpha. \tag{4.8}$$

As in multinomial logit, all terms are identified except for a base β_j. Note that the family size N helps in identification in that it identifies ψ from γ. Other researchers have tried to measure the effect of family size on care choices by including N as a linear explanatory variable. Note that in equation (4.8) family size affects choices in that it determines the number of options in the choice set and it interacts with other explanatory variables. The structure in equation (4.8) implies that a semiparametric specification of the choice probability would have to include X_0, each X_j, each $\sum_i Q_{ij}$, and N as separate arguments in the unspecified functional form. This result is independent of how we specify the participation decision of each child and would hold for a large class of side-payment rules. Since such a semiparametric specification is not feasible to estimate, added structure

[23] Explanatory variables remain constant, and caregiver choice is independent over samples.

is needed in order to capture the effects of family characteristics specified in equation (4.1).

4.4. Testing

The model can be tested using the data on side payments made by children to the parent. Consider partitioning the data into K groups and let $Q_{kn} = 1$ if the parent in the nth family of the kth group receives a side payment. The data contain the realizations of Q_{kn} over n.[24] Let $R_{kn}(\theta) = \Pr[Q_{kn} = 1 \mid \theta_0] = EQ_{kn}$ where θ_0 is the true value of θ. Define $Q_k = \sum_n Q_{kn}$ and $R_k(\theta) = \sum_n R_{kn}(\theta)$ by aggregating within each group. Then stack Q_k and $R_k(\theta)$ over k to construct Q and $R(\theta)$. The vector $R(\theta_0)$ is not observed; instead $R\left(\hat{\theta}\right)$ is observed. Rewrite

$$Q - R\left(\hat{\theta}\right) = [Q - R(\theta_0)] - \left[R\left(\hat{\theta}\right) - R(\theta_0)\right]. \tag{4.9}$$

By construction, $E[Q - R(\theta_0)] = 0$ and $\text{plim}\left[R\left(\hat{\theta}\right) - R(\theta_0)\right] = 0$. Let $\mathfrak{D}[\cdot]$ indicate the covariance matrix of a random vector. Then

$$\mathfrak{D}\left[Q - R\left(\hat{\theta}\right)\right] = \mathfrak{D}[Q - R(\theta_0)] + \mathfrak{D}\left[R\left(\hat{\theta}\right) - R(\theta_0)\right] \tag{4.10}$$

$$= \text{diag } R(\theta_0)[I \text{ - } \text{diag } R(\theta_0)] + \frac{\partial R(\theta_0)'}{\partial \theta} \mathfrak{D}\left[\hat{\theta}\right] \frac{\partial R(\theta_0)}{\partial \theta} \tag{4.11}$$

using the methodology described in Heckman (1980). In Heckman (1980), the second covariance term is subtracted because the data used to perform the goodness-of-fit test are also used to estimate θ. This causes a nonzero covariance between $Q - R(\theta_0)$ and $R\left(\hat{\theta}\right) - R(\theta_0)$. We assume

[24] Actually, the data specify which child made the side payment, but it is easier to use the Q_{kn} variable.

this covariance is zero because the side payment data were not used to estimate θ. However, if the side payment data are correlated with the care provision data, then our assumption is incorrect. One can construct a chi-square statistic as

$$\left[Q - R\left(\hat{\theta}\right)\right]' \left(\mathfrak{D}\left[Q - R\left(\hat{\theta}\right)\right]\right)^{-1} \left[Q - R\left(\hat{\theta}\right)\right] \sim \chi^2_K. \tag{4.12}$$

Also

$$\left[Q_k - R_k\left(\hat{\theta}\right)\right]' \left(\mathfrak{D}\left[Q_k - R_k\left(\hat{\theta}\right)\right]\right)^{-1} \left[Q_k - R_k\left(\hat{\theta}\right)\right] \sim \chi^2_1 \tag{4.13}$$

(where $\mathfrak{D}\left[Q_k - R_k\left(\hat{\theta}\right)\right]$ is defined analogously to equation (4.11)) can be used to search for poor fits in particular regions of the data.

5. Results

The variables included in the model are as follows. The parent variables in X_0 of equation (4.1) are a constant, gender (FEMALE), age (AGE), education (EDUC), marital status (MARRY), race (BLACK), activities of daily living problem (ADL) variables (ADBED, ADBTH, ADDRS, ADEAT, ADWKI, and ADTLT), and state Medicaid characteristics (PROGRAM, RESLIM, and INCLIM).

Previous research (see, for example Wolf and Soldo 1988 or Stern 1995) shows that the following people are less likely to live alone: women, older people, single people, and people with ADL problems (see also Hing and Bloom 1990 or Kovar 1988). The results with respect to race and education (a proxy for income) are less clear. Stern (1995) finds that a black child is less likely to provide care to an elderly parent while some previous work finds the opposite (see Wolf 1984 or Spear and Avery 1993). Michael et al. (1980), Crimmins and Ingegneri (1990), and Wolf and Soldo (1988) find that care by children declines with parent income, but Pampel (1983) and Wolf

(1984) find the opposite. Stern (1995) finds that parental education has no significant effect on care provision.

The three included Medicaid program characteristics measure the generosity of eligibility rules allowing Medicaid to pay for nursing home expenses. In order to have Medicaid pay for nursing home expenses, the elderly parent must spend down her assets to a resource limit (RESLIM) that varies across states. Then she is eligible if her income is below an income limit (INCLIM) that varies across states. Some states have a "medically needy program" that allows the parent to deduct medical expenses (including nursing home expenses) from income before comparing income to the income limit. The PROGRAM dummy identifies states with a "medically needy program." These three variables capture the variation in Medicaid in only a crude way. Many of the details of these programs are described in more detail in, for example, Cutler and Sheiner (1993).

The children variables included in the model are gender (FEMALE), age (AGE), marital status (MARRY), distance measures (DIST_i, $i = 1, 2, ..., 5$), work status (WORK) and spouse's work status (SWORK), number of grandchildren (CHILD), and dummies for the oldest male (OMC) and oldest female (OFC) children. Previous literature suggests (see, for example, Horowitz 1985) that older, single, female children without jobs and living close to the parent are the most likely caregivers. Some of the literature (see, for example, Treas, Gronvold, and Bergtson 1980) suggests that being the oldest daughter makes one especially likely to provide care. After controlling for endogeneity, Stern (1995) finds that distance is the only significant predictor of care provision among child characteristics. Almost all other variables in Stern (1995) have correct signs but are not statistically significant.

The child variables in this model are allowed to affect care provision in three different ways. First, X_j affects V_{ij} in equation (4.1) through $X_j\psi$ in that each family member cares about j's characteristics because they affect the quality of care the parent will receive. The child characteristics in $X_j\psi$, called family effects, are distance variables (DIST_i, $i = 1, 2, ..., 5$), WORK, SWORK, CHILD, OMC, and OFC. Second, if i is the caregiver, then i's characteristics affect the burden i will sustain in providing care. This is measured in $X_j\gamma\delta_{ij}$. The child characteristics in $X_j\gamma\delta_{ij}$, called own effects, are FEMALE, AGE, MARRY, SWORK, CHILD, OMC, OFC, and the distance variables. Finally, each child may have an idiosyncratic relationship with each other child. We assume their effects on V_{ij} can be measured through differences between X_i and X_j denoted by $Q_{ij}\alpha$ in equation (4.1). Variables included here, called idiosyncratic relationship effects, are SEX (= 1 if i and j have opposite sex), AGE (= absolute value of difference in age), AGEO (= 1 if j is older than i), MARRY (= 1 if i and j do not have the same marital status), MNDIST (= minimum possible distance between i and j), MXDIST (= maximum possible distance between i and j)[25] and WORK (= 1 if i and j do not have the same work status).

The parameter estimates along with estimated standard errors are reported for the voluntary model in Table 2. Variables with an N-prefix apply to nursing homes, variables with an A-prefix apply to living alone, variables with a CF-prefix apply to the family ($X_j\psi$) children effects, variables with a CO-prefix apply to the own ($X_j\gamma\delta_{ij}$) children effects, and variables with a CD-prefix apply to the idiosyncratic relationship ($Q_{ij}\alpha$) children effects. The bootstrap-like simulations discussed below equation (4.7) show that bias is small and statistically insignificant and that standard errors are relatively small. Table 3 shows the total effect of each child variable for families of varying size. While some of the child variables have own effects and family effects of different signs in Table 2, the total effect of the variable is significant. Results are generally consistent with prior expectations.

[25] Distances are observed only between each child and the parent. Given this information we can construct MNDIST and MXDIST as proxies for the true distance between i and j.

In particular:

a) Women are more likely to live with children (N-FEMALE and A-FEMALE are negative).

b) As people age, they are more likely to enter nursing homes and less likely to live alone (N-AGE > 0 and A-AGE < 0).

c)People with more education are less likely to live with children but by small amounts (N-EDUC > 0 and A-EDUC > 0).

d) People with spouses are more likely to live alone (A-MARRY > 0).

e) Black people are more likely to live alone (A-BLACK> 0). Other work suggests that blacks are less likely to live alone. In fact, a crosstabulation of living arrangement with race in this data shows that 48.6% of white parents received no help and 33.5% of black parents received no help in 1984. Even after conditioning on family size, blacks are less likely to receive no help. However, one must also condition on other family characteristics. For example, a higher proportion of the black sample is female than of the white sample. Since A-FEMALE < 0, the difference in sex distribution helps explain the difference between conditional and marginal care proportions. In fact, except for A-ADBED, every parent variable helps explain this difference. For the children variables, the effects are mixed. Still, it is clear that variation in family characteristics helps cause a correlation between race and care choices that makes evaluation of crosstabs inappropriate.

f) The existence of problems dressing (A-ADDRS), using a toilet (A-ADTLT), or walking (A-ADWKI) decrease the value of living alone. The signs on the ADL's associated with getting out of bed (A-ADBED), bathing (A-ADBTH), or eating (A-ADEAT) are incorrect and mostly significant, though.

g) Increasing Medicaid income and resource limits increase the value of entering a nursing home (N-INCLIM > 0 and N-RESLIM > 0). But the existence of a "medically needy program" decreases it by a statistically insignificant amount. Part of the reason the government policy effects are small is because Medicaid does not pay for all nursing home stays. Levit, et al. (1985) report that only 49.1% of nursing home expenditures were paid for by Medicaid in 1984. Also, families have devised ways to circumvent the Medicaid nursing home rules.

h) Children who live close to the parent and do not work or whose spouse does not work are perceived by other family members as being able to provide good care (in Table 2, CF-DIST$_i$ decreases with i for $i \leq 4$, CF-WORK < 0, and CF-SWORK < 0.

i) Family members perceive the oldest daughter as not being able to provide the best care (CF-OFC < 0), but the oldest daughter has less burden associated with caregiving (CO-OFC > 0). The same qualitative results are true for oldest sons (CF-OMC < 0, CO-OMC > 0).

j) The burden associated with caregiving is smaller for women (CO-FEMALE > 0), younger children (CO-AGE < 0), nonworking children (CO-WORK < 0), and children with working spouses (CO-SWORK > 0).

k) Marital status differences (CD-MARRY), sex differences (CD-SEX), birth order (CD-AGEO), and distances between children (CD-MNDIST and CD-MXDIST) are the best predictors of idiosyncratic relationships among children. However, the results predict that children prefer the caregiver's marital status to be different from their own (CD-MARRY > 0), and the two distance effects, MNDIST or MXDIST, have opposite signs when included in the same model.

l) Total effects of children variables, reported in Table 3, indicate that children with the following characteristics are preferred caregivers: close children (C-DIST; decreases with i), and nonworking children (C-WORK < 0). Other effects are not consistent across family size.

Analogous results for the collective model are reported in Tables 4 and 5. While most signs are the same, coefficients are generally smaller, and fewer are significant. In particular, the parent's gender and marital status and the child's gender and total distance effects become less significant.

The collective and voluntary models are not nested. Nevertheless, their explanatory power can be compared by constructing statistics of the form $\left(y^k\right)' \left[\mathfrak{D}\left(y^l\right)\right]^{-1} \left(y^k\right)$ where y^k is the vector of residuals used in equation (4.4) for model k (collective or voluntary) and $\left[\mathfrak{D}\left(y^l\right)\right]^{-1}$ is the inverse covariance matrix of y^l. If model k is correctly specified, then the statistic should be distributed χ^2_q where q is the number of residuals. These quadratic forms are reported in Table 6. The "uncensored" statistics are the quadratic forms, and the "censored" statistics censor each family statistic at the 0.001% significance level to control for outliers. The difference between the two columns shows that there are significant outliers, especially when the collective inverse covariance matrix is used. Using the uncensored statistics allows a small number of observations to dominate the test statistic. Use of the censored statistic acknowledges the existence of the outliers (and therefore rejection of the null hypothesis), but allows one to ask the more interesting questions about the sample as a whole. When the censored quadratic forms are used, each model outperforms the other when its own inverse covariance matrix is used. Thus, neither model clearly outperforms the other. However, both models are consistent with the data after controlling for outliers.

The kernel-smoothed density of residuals, disaggregated by family size, is presented in Figure 1. The model predicts large family care choices well but misses more often on small families (size ≤ 2). In particular, it underpredicts individuals with no children living alone, and residuals for families with one child (size $= 2$) have a large variance.

We can disaggregate the residuals by state of residence of the parent to look for state effects. Figure 2 shows the distribution of state average living alone and nursing home residuals. A chi-square statistic for each state with two degrees of freedom can be constructed to test for the significance of state average residuals. Only the test statistics for starred states are significant.

The statistics can be added to construct a χ^2_{86} statistic.[26] This statistic is equal to 1308.33 but mostly because of Tennessee's $\chi^2_2 = 1163.56$. If, as was done in Table 6, we censor the outliers at the 0.001% significance level, the χ^2_{86} becomes 90.72 which is not significant. There is no obvious pattern to the placement of states in Figure 2. Thus, there seems to be no evidence of missing state effects.

We regressed log family χ^2 statistics on parent characteristics to look for missed relationships. We included log of family size, sex, race, age, marital status, number of ADL's of the parent, and dummies for whether the chosen care alternative was living alone or living in a nursing home. Using OLS, we generally found statistically significant coefficients. But the only coefficients with any magnitude were those associated with log of family size (family size increases degrees of freedom of the χ^2 statistic) and the dummies for the care alternative chosen (which is the dependent variable). Thus, there are no obvious places to look for missing explanatory power.

There is a small sample of 36 families living alone in the first year which was not used to estimate the model because we were not confident enough of some of the imputed values for these observations. However we can use these observations to construct a small out-of-sample χ^2 test. The statistics analogous to the in-sample test in Table 6 are reported in the first panel of Table 7. As in Table 6, there is evidence of outliers, and, after controlling for outliers, neither model is rejected.

There is also a sample of 723 families who were not living alone in the first year. The χ^2 tests for these are reported in the second panel of Table 7. All statistics are significant except for the censored voluntary residuals using the voluntary covariance matrix. In all but this case, the

[26]There are 43 states and the District of Columbia with observations from the data. Each jurisdiction contributes two degrees of freedom, and two degrees of freedom are lost due to adding up constraints.

model is formally rejected by these out-of-sample data even though the model explains the data reasonably well. However, Stern (1995) estimates a less structural but qualitatively similar model and finds that parameter estimates are significantly different when the model is estimated with the extra 723 families relative to not including them. Stern's (1995) results probably occur because the probability of living alone in 1984 depends upon what care the parent was receiving in 1982. It is not clear why we do not observe the same phenomenon.

Another way to test the model is with the side-payment data described in Table 8. The side payment data we use is the existence of at least one child paying for some lodging or medical bills of the parent. As indicated in Section 3, there are also data on children other than the primary caregiver providing help; we could treat such events as sidepayments but choose not to. Obviously, families with no children (Family Size = 1) have no side payments because there are no children to make them. More surprising is that in families with one child (Family Size = 2), side payments are very rare. Side payments occur frequently only in large families (19.6% of the sample). Large white families (24.8%) are more likely to have side payments than large black families (15.8%).

The results of the side-payment χ^2 goodness-of-fit tests described in equations (4.12) and (4.13) are in Table 9. Results are disaggregated by race, sex, family size, and predicted deciles of the probability of the parent receiving a side payment. We systematically overpredict side payments (the overall mean residual is -.321). We report "corrected" χ^2 statistics using the covariance matrix in equation (4.11) and "uncorrected" χ^2 statistics using only the first term in equation (4.11). The uncorrected overall χ^2_{39} statistic is 307.13 which is very significant. The corrected χ^2_{39} statistic is 255.68 which is still significant. The difference occurs mostly because the variation in $\hat{\theta}$ causes large positive covariances among the $Q_k - R_k\left(\hat{\theta}\right)$ terms which cause the corrected χ^2_{39} statistic to be smaller. However, the significance of the corrected statistic is mostly due to the cells in the three highest deciles. If they are excluded, then the χ^2_{25} statistic is 92.87 (when standardized, it is 9.60 which is still very significant). Table 10 shows that we are doing poorly only for high deciles; the χ^2 statistics increase and the mean residuals increase in absolute value.

We may be overpredicting side payments because the model is misspecified. But we also may not be observing all side payments. In particular, we observe side payments only in the form of providing lodging or paying bills. Bernheim, Schleifer and Summers (1985) suggest side payments sometimes can be made in the form of personal attention. The sociology literature shows that financial cost is not a major part of the burden of caregiving (Horowitz and Shinkelman 1983), side payments tend to be small (Schoonover, et al. 1988) or made to children (Morgan 1982 and Hoyert 1991), and that side payments are made in the form of additional help (Matthews and Rosner 1988 and Coward and Dwyer 1990). Obviously including the extra help provided by other children as sidepayments would help our results here.

6. Simulation Experiments

The magnitudes of the results in Tables 2 through 5 are difficult to interpret because their effect on care probabilities is nonlinear. We simulated a representative sample of one million families with a parent aged seventy years old or older using data from other sources to set the parameters of the joint density of the family characteristics. Details are given in Stern (1995). The simulated sample is described in Table 11.

The care alternatives are grouped into living with a spouse but with no help from children, living without a spouse and with no help from children, living in a nursing home, or receiving care from a child. The two significant differences between the simulated sample and the Long-Term Care Survey sample is parents have many fewer ADL's in the simulated sample, and being cared for by children is not as common an option in the simulated sample. The latter difference is caused by the former. The former occurs because having an ADL is a screening criterion for inclusion in the Long-Term Care Survey.[27]

One can use the estimated model to simulate the effects on care provision of various experiments. Many interesting experiments have been suggested by previous literature. For example, Treas (1977) has argued that declining fertility rates will lead to fewer children providing care. Table 12 shows the effect of decreasing family size on care choices. In the baseline case, family size is set by drawing a standard uniform random variable and then transforming it into a family size using the inverse empirical family size distribution. In the experiment, the uniform random variable is multiplied by 0.8, deflating family sizes by 0.29 children on average. As can be seen in Table 12, this makes it less likely that children will provide care and more likely the other alternatives will be used. However, the absolute changes and associated elasticities are relatively small.

Treas (1981) suggests that increasing labor force participation rates of women will reduce care by children. The small coefficients on work related variables in Tables 2-5 suggest this effect also is small.

Crimmins and Ingegneri (1990) suggest that child migration will affect care arrangements. We performed two simulations to measure this effect. In the first, we shifted children who lived an intermediate distance to living long distances (Pr[DIST4] decreases 10% and Pr[DIST5] increases 10%). This had only very small effects on care arrangements because children living relatively far away were not likely care providers anyway. The second experiment shifts geographically close children to intermediate distances (Pr[DIST0] decreases 3%, Pr[DIST1] decreases 9%, Pr[DIST2] increases 8%, and Pr[DIST3] increases 4%). The changes in care provision are displayed in Table 13.

[27] ADL's are simulated based on probit parameters estimated from the 1979 National Health Interview Survey.

Again changes occur in expected directions (children reduce caregiving) but by modest amounts.

We also considered the effect of longer life expectancies on care provision. Fixing the original joint density of sex, race, and age of parents in 1982, we decreased two-year death probabilities of parents and children by 50%. The effect of this experiment on family characteristics is to increase the size of families, the age of children, the probability of a child being married, and the average age of parents all by small amounts (see Note 1 of Table 14). The effect on care provision, controlling for parent's age, is displayed in Table 14. The largest effect is due to the spouse of the parent remaining alive longer. The effect on children providing care is negligible. The other significant effect of decreasing death probabilities, not captured here, is to shift the age distribution of parents towards more elderly people.[28] Making the parent population older would also increase the prevalence of ADL's. These effects are observed in Table 14 only by measuring the change in care choices across age groups.

Finally, we considered the effect of doubling the Medicaid Resource Limit from $1000 to $2000. Results, listed in Table 15, show that this makes nursing homes a more frequent choice but only by small amounts.[29]

All of the simulation results reported so far concern two year transition probabilities. The reader might wonder how they translate into long-run care probabilities. Stern (1995) gets similar results for 2 year transition possibilities and shows that they result in only moderate long run effects.

All of the experiments we performed had the expected directional effect. But none can explain the magnitude of the secular trend away from care provision by children toward the other alternatives. This suggests there must be other secular changes in society that have not been captured in

[28]This effect is missing in Table 14 because we do not allow the joint density of sex, race, and age in 1982 to be affected by the change in death probabilities.

[29]Given the experiment, the numbers of Table 15 are both level changes and elasticities.

our cross-section study.

7. Family Welfare Simulations

One might consider how different side-payment rules would affect family utility. Table 16 shows the effect on family utility and mean side payments of five side payments rules. The first panel uses the side-payment rule used to estimate the voluntary model (the split-the-rents rule). Parent utility and mean child utility increase as family size increases because there are more options available to the family. Net side payments to the parent are small.

Consider the alternative (utilitarian) rule where side payments are chosen to maximize the sum of family members' expected utilities subject to the constraint that the parent has incentive to attend the meeting:

$$U_0 \geq \max\left[V_{00}, V_{0,-1}\right] \tag{7.1}$$

where U_0 is the parent's utility defined in equation (2.4) and the right-hand side of equation (7.1) is the parent's best alternative if she acts independently of her children.[30] As is true in all of the experiments, parent utility does not change if there are no children because no side payments are feasible. For families with children, the utilitarian rule leads to side payments that are small on average but make children better off and parents usually worse off. Note, however, that the differences in mean utility between the split-the-rents rule and the utilitarian rule are small relative to the standard deviations of utility. Consider a side payment designed by the parent to maximize her own expected utility. Such a rule implies significantly larger side payments, and they are

[30]Without the constraint, the maximum occurs at a point where the parent bankrupts herself making side payments to children. This occurs because the side payments have no direct effect on the sum of utilities but increase the probability of children attending the meeting.

generally from the children to the parent. They are still limited in size by the childrens' ability to be absent from the family meeting.

The side-payment rule where each participating family member receives her Shapley value is very similar to the split-the-rents rule. In fact, the two rules are identical for all two-person families and 908 out of 1256 larger families.

A world in which no side payments could occur would make the parent worse off but would make the average child better off relative to the split-the-rents rule, and it would make almost all family members worse off relative to the utilitarian rule.

The split-the-rents rule, the Shapley rule, and the no-side-payments rule are each Pareto dominated by one of the two Pareto efficient rules for some families. Thus, they are not themselves Pareto efficient.

8. Conclusions

The goal of this paper is to specify and estimate an equilibrium model of family decision making. The steps involved are specification of each family member's utility function, the actions available to each family member, and an equilibrium mechanism. Ideally, adding randomness in appropriate places will ensure that the data can be explained by the model, that an equilibrium exists and is unique, and that the statistical objective function is smooth in parameters.

Inclusion of our family participation error e_i solves the equilibrium problems and alleviates but does not eliminate the other two problems. Our model estimators and simulations are quite robust to details of model specification concerning collective or voluntary behavior and side payment rules. On the one hand, this suggests that researchers may be able to choose model specification details to deal with other issues such as existence of equilibrium and computational feasibility without undue concern. On the other hand, one must worry that some implications of the model depend upon details of its specification and that the data may not be able to identify such details.

An alternative estimation strategy would be to specify family decisions as nonparametric or semiparametric functions of family characteristics. The model used here and the results in Stern (1995) and here suggest that such an approach would be difficult to implement. In particular, one would have to allow for interactions of family size and family structure with other family characteristics; the curse of dimensionality would doom such an approach.

Our estimation results are quite robust with respect to model specification. Yet they allow us to perform interesting experiments concerning the effect on care probabilities, side payments, and family utility of various demographic, government, or economic changes. Unfortunately, our model does not explain the large secular changes in care provision that have occurred over the last generation. This is a common problem associated with using cross-section data to predict long-term behavior. Thus, there is a need to extend such models to long-term behavior and panel data.

Appendix A

Pareto Efficient Side Payments

The parent's expected payoff is

$$EV^0 + \sum_{j>0} p_j m_j, \tag{A.1}$$

and (from the planner's point of view) child j's expected payoff is

$$EV^j - p_j m_j + \int_{t_j}^{\infty} e dF_j(e) \tag{A.2}$$

The planner's problem is to maximize

$$w_0 \left(EV^0 + \sum_{j>0} p_j m_j \right) + \sum_{j>0} w_j \left(EV^j - p_j m_j + \int_{t_j}^{\infty} e dF_j(e) \right) \tag{A.3}$$

subject to

$$t_j = m_j - \Delta_j V^j \tag{A.4}$$

and

$$p_j = 1 - F_j(t_j) \tag{A.5}$$

for all $j > 0$. The Lagrangian is:

$$\begin{aligned} &\sum_{j \geq 0} w_j EV^j + \sum_{j>0} \left[(w_0 - w_j) p_j m_j + w_j \int_{t_j}^{\infty} e dF_j(e) \right] \\ &+ \sum_{j>0} \left\{ \lambda_j \left[1 - p_j - F_j(t_j) \right] + \mu_j \left(t_j - m_j + \Delta_j V^j \right) \right\}. \end{aligned} \tag{A.6}$$

The first-order conditions are obtained by differentiating with respect to m_i, t_i, and p_i (respectively):

$$w_0 p_i - w_i p_i - \mu_i = 0, \tag{A.7}$$

$$-w_i t_i f_i\left(t_i\right) - \lambda_i f_i\left(t_i\right) + \mu_i = 0, \tag{A.8}$$

and

$$\sum_{j \geq 0} w_j \Delta_j V^j + \left(w_0 - w_i\right) m_i - \lambda_i + \sum_{\substack{j > 0 \\ j \neq i}} \mu_j \Delta_{ij} V^j = 0 \tag{A.9}$$

where f_i is the derivative of F_i and $\Delta_{ij} V^j$ denotes $E_{ij}\left\{\left[V^j_{S \cup \{i,j\}} - V^j_{S \cup \{j\}}\right] - \left[V^j_{S \cup \{i\}} - V^j_S\right]\right\}$.

Only the last of these requires any explanation. Because

$$EV^j = p_i E_i V^j_{S \cup \{i\}} + \left(1 - p_i\right) E_i V^j_S, \tag{A.10}$$

$$\partial EV^j / \partial p_i = E_i \left[V^j_{S \cup \{i\}} - V^j_S\right] = \Delta_i V^j. \tag{A.11}$$

Similarly, because $\Delta_i V^j = p_j E_{ij} \left[V^j_{S \cup \{i,j\}} - V^j_{S \cup \{j\}}\right] + \left(1 - p_j\right) E_{ij} \left[V^j_{S \cup \{i\}} - V^j_S\right]$, for $j \neq i$

$$\partial \Delta_i V^j / \partial p_j = \Delta_{ij} V^j. \tag{A.12}$$

Combining the first order conditions gives

$$\begin{aligned}&\sum_{j\geq 0} w_j \Delta_i V^j + (w_0 - w_i)\left[\Delta_i V^i - p_i / f_i\left(t_i\right)\right] + w_0 t_i + \\ &\sum_{\substack{j>0 \\ j\neq i}} (w_0 - w_j)\, p_j \Delta_{ij} V^j = 0.\end{aligned} \tag{A.13}$$

Appendix B

Shapley Value

Let A denote the set of family members and, for each $M \subset A$, let V_M denote $\sum_{i \in M} V_M^i$, the maximum total payoff attainable by the subset M. Instead of using V_M, we could use any function v_G defined on subsets of A to represent the total amount that the subset M would be able to divide among its members (with $v_G(\phi) = 0$). The function v_G is said to represent the game G. A solution concept attributes a payoff $\pi_G(i)$ to each member $i \in A$.

The Shapley value is the only solution concept to satisfy the following four requirements:

1. Symmetry: If two games are identical except that the identities of the players are permuted, then the payoffs are the same except that the identities of the players are permuted.

2. Pareto efficiency: The sum of all players' payoffs is $v_G(A)$.

3. If player i's marginal contribution to every coalition is zero, then i's payoff is zero: If $v_G(S \cup \{i\}) = v_G(S)$ for all $S \subset A$, then $\pi_G(i) = 0$.

4. The payoff function is linear: If $\lambda \in [0,1]$, and G and G' are games represented by v_G and $v_{G'}$ respectively, let G" denote the game represented by $\lambda v_G + (1-\lambda) v_{G'}$. Then $\pi_{G"} = \lambda \pi_G + (1-\lambda) \pi_{G'}$.

Appendix C

Estimation Details

C.1. Solving for Equilibrium p_i's

Equations (4.1), (4.2), and a rent sharing rule define an environment. Equation (2.13) defines a set of thresholds $\{t_i\}$ given the environment, and equation (2.14) provides p_i given t_i for each i. It is still necessary to provide an algorithm to solve for the equilibrium p_i's. Four different algorithms are used at one point or another in the estimation program. The first is a Gauss-Seidel method with progressive dampening. In particular, let p^k be the kth step approximation of the vector of p_i's and $t\left(p^k\right)$ be the vector of threshold values implied by p^k using equation (2.13). Applying equation (2.14) to $t\left(p^k\right)$ gives a new approximation of p. We take a convex combination of the new approximation and p^k,

$$p^{k+1} = \omega\left[1 - F\left(t\left(p^k\right)\right) - p^k\right] + p^k \tag{C.1}$$

If $\omega = 1$, there is no dampening. We let ω decrease as k increases.[31] Convergence is reached when $\left|p^{k+1} - p^k\right|$ is smaller than a specified tolerance. This method works very efficiently almost all of the time. An alternative is to invert $1 - F\left(t\left(p^k\right)\right)$ and iterate over threshold values. This method works efficiently frequently when the first does not. Which works better depends upon the vector of derivatives $(\partial F/\partial t)(\partial t/\partial p)$. If neither of the two converges, we use a Gauss-Newton routine. Finally, all three of these may fail to converge in a reasonable time, especially when σ_e is small.

[31] If ω becomes too small or k becomes too large, we try a different solution method.

The last algorithm is a Richardson extrapolation routine especially suited to this case. Let $P(\sigma_e)$ be the equilibrium p as a function of σ_e. Assume for σ_e, $P(\sigma_e)$ can not be found with the Gauss-Seidel algorithm, but $P(2\sigma_e)$, $P(3\sigma_e)$, and $P(5\sigma_e)$ can be found. Then Taylor series approximations around $P(\sigma_e)$ are:

$$P(2\sigma_e) = P(\sigma_e) + \sigma_e P^{(1)}(\sigma_e) + \frac{\sigma_e^2}{2} P^{(2)}(\sigma_e) + O\left(\sigma_e^3\right) \tag{C.2}$$

$$P(3\sigma_e) = P(\sigma_e) + 2\sigma_e P^{(1)}(\sigma_e) + \frac{4\sigma_e^2}{2} P^{(2)}(\sigma_e) + O\left(\sigma_e^3\right) \tag{C.3}$$

$$P(5\sigma_e) = P(\sigma_e) + 4\sigma_e P^{(1)}(\sigma_e) + \frac{16\sigma_e^2}{2} P^{(2)}(\sigma_e) + O\left(\sigma_e^3\right) \tag{C.4}$$

where $P^{(i)}(\sigma_e)$ is the ith derivative of P evaluated at σ_e. Equations (C.2), (C.3), and (C.4) can be manipulated to get

$$P(\sigma_e) = \frac{8}{3} P(2\sigma_e) - 2P(3\sigma_e) + \frac{1}{3} P(5\sigma_e) + O\left(\sigma_e^3\right) \tag{C.5}$$

C.2. Derivatives of Residuals

We need to be able to differentiate EY_n (defined below equation (4.3)) with respect to θ for instruments and the estimation algorithm. There are two difficulties associated with evaluating these derivatives. The first is that the equilibrium p vector is the solution to a nonlinear equation that can not be solved exactly. Thus we use a second order Taylor series approximation to the derivatives. Let $G(p, V) = p$ describe equilibrium in terms of p and the vector of V_{ij}'s. Then

$$dp/dV = \left[I - G_p + (b' \otimes I) \frac{\partial vecG_p}{\partial p}\right]^{-1} \cdot \left[G_v - (b' \otimes I) \frac{\partial vecG_p}{\partial v}\right] \tag{C.6}$$

where b' is the difference between the approximation and the true equilibrium p. Since b' is typically very small, the second order terms have only small effects. However, there are families and parameter values where second order effects matter.

The second difficulty is that, while the set of points where derivatives fail to exist is of measure zero, our estimation algorithm performs poorly even when nearby such points. These points occur when, for example, $j^*(M)$ in equation (2.5) for some M changes with small changes in θ. This causes severe problems in using derivative-based optimization algorithms and in computing an estimate of the covariance matrix of the parameter estimates.

Because of the nondifferentiability problem, we use an estimation algorithm that switches between a quasi-Newton method and the simplex method in GQOPT. The simplex method pushes the parameter values away from points of nondifferentiability, and the quasi-Newton method takes efficient steps until it gets near a new point of nondifferentiability where derivatives are not informative.

Appendix D

Solution of Parent's Side

Payment Problem with Bequests

Let $C = A \backslash \{0\}$ be the set of all children. The parent's problem conditional on a total bequest B is

$$\max_{\tilde{s}} E_0 V_M^0 \tag{D.1}$$

subject to

$$s_i(M) \leq 0 \text{ if } i \notin M \quad \forall i,\ \forall M \subset C; \text{ and} \tag{D.2}$$

$$\sum_{i \in C} s_i(M) = -B \qquad \forall M \subset C \tag{D.3}$$

where M is a subset of the children, $\tilde{s} = \{s_i(M)\}_{i \in C,\ M \subset C}$, and $s_i(M)$ is the side payment from i to the parent conditional on the subset of children participating being equal to M. We require that the parent's total bequest is equal to B no matter which children, if any, participate in the care decision.

Consider first a family with two children so that $C = \{1, 2\}$.[32] Let $\tilde{s}_0 = -s_1(\emptyset)$, $\tilde{s}_1 = -s_1(\{1\})$, $\tilde{s}_2 = -s_1(\{2\})$, and $\tilde{s}_3 = -s_1(\{1, 2\})$ be the vector of side payments to child 1 conditional on M. The side payments to child 2 are given by equation (D.3). Child 1 cares only about

$$\Delta m_1 = p_2(\tilde{s}_3 - \tilde{s}_2) + (1 - p_2)(\tilde{s}_1 - \tilde{s}_0), \tag{D.4}$$

[32]As in Bernheim, Shleifer, and Summers (1985), this model has little to say about families with one child.

and child 2 cares only about

$$\Delta m_2 = p_1 \left(\tilde{s}_1 - \tilde{s}_3 \right) + \left(1 - p_1 \right) \left(\tilde{s}_0 - \tilde{s}_2 \right). \tag{D.5}$$

Assume the parent's expected utility increases in p_1 and p_2. Suppose, for simplicity, that it increases in Δm_1 and Δm_2. The set of feasible combinations of Δm_1 and Δm_2 is defined by p_1, p_2, and equation (D.2) and looks like the shaded region in Figure 3 where points in the interior are dominated by points on the boundary. Thus the parent's optimal strategy is to pick the point on the curve in Figure 3 that maximizes equation (D.1).

When there are more than two children, the curve in Figure 3 is replaced by a surface. In general, since the equation(s) representing the curve are difficult to manipulate, solution of this problem is computationally expensive.

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Table 1

Sample Moments for 1984 Data

Parent Variables Variables	Definition	Mean	St. Dev.
	Living with Children	0.155	0.362
	Living in Nursing Home	0.086	0.281
	Living Home Alone	0.759	0.428
FEMALE	Female	0.619	0.486
AGE	Age	77.35	6.96
EDUC	Education	9.33	3.79
MARRY	Married	0.510	0.500
BLACK	Black	0.098	0.298
ADBED	ADL Problem - Bed	0.172	0.377
ADBTH	ADL Problem - Bathing	0.320	0.467
ADDRS	ADL Problem - Dressing	0.201	0.401
ADEAT	ADL Problem - Eating	0.091	0.288
ADTLT	ADL Problem - Toilet	0.156	0.363
ADWKI	ADL Problem - Walking Inside	0.156	0.363
PROGRAM	State has a Medically Needy Program	0.497	0.500
RESLIM	State Countable Resource Limit	19.352	5.306
INCLIM	State Income Limit/1000	0.0037	0.0048
	Number of Children	1.424	
Child Variables Variable	**Definition**	**Mean**	**St. Dev.**
FEMALE	Female	0.460	0.498
AGE	Age	44.89	13.60
MARRY	Married	0.832	0.375
DIST1	Distance from Parent Dummy 1	0.181	0.385
DIST2	Distance from Parent Dummy 2	0.185	0.388
DIST3	Distance from Parent Dummy 3	0.097	0.296
DIST4	Distance from Parent Dummy 4	0.295	0.456
DIST5	Distance from Parent Dummy 5	0.151	0.358
WORK	Child Works	0.668	0.471
SWORK	Child's Spouse Works	0.593	0.491
CHILD	Number of Child's Children	0.684	1.079

Notes:

1. Sample size is 1952.

2. The PROGRAM variable is from Cutler and Sheiner (1993), Table 3, Column 1.

3. The RESLIM variable and the INCLIM variable are from Neuschler and Gill (1986), Table 1, Pg. 11.

4. Distance dummies for children are 0 = living with parent (base choice), 1 = 1 to 10 minutes, 2 = 11 to 30 minutes, 3 = 31 to 60 minutes, 4 = 61 minutes to less than 1 day, and 5 = greater than or equal to 1 day.

5. Reported SWORK moments are conditional on a spouse being present.

Table 2

Parameter Estimates for Voluntary Model

Variable	Estimate	Variable	Estimate	Variable	Estimate
N-CONSTANT	-1.516** (0.028)	A-ADWKI	-0.143** (0.015)	CO-DIST1	-1.229** (0.058)
A-CONSTANT	0.314** (0.012)	N-PROGRAM	-0.055 (0.034)	CO-DIST2	-0.655** (0.035)
N-FEMALE	-0.159** (0.049)	N-RESLIM/10	0.055 (0.066)	CO-DIST3	-0.295** (0.071)
A-FEMALE	-0.087** (0.011)	N-INCLIM	0.002 (0.031)	CO-DIST4	-0.421** (0.092)
N-AGE/10	0.066** (0.024)	CF-DIST1	0.127** (0.044)	CO-DIST5	-1.974** (0.451)
A-AGE/10	-0.093** (0.006)	CF-DIST2	-0.211** (0.021)	CO-WORK	-0.093** (0.036)
N-EDUC	0.007 (0.005)	CF-DIST3	-0.473** (0.041)	CO-SWORK	0.963** (0.043)
A-EDUC	0.005** (0.002)	CF-DIST4	-0.572** (0.042)	CO-CHILD	0.071** (0.022)
N-MARRY	0.006 (0.041)	CF-DIST5	-0.096 (0.242)	CO-OMC	0.904** (0.060)
A-MARRY	0.176** (0.014)	CF-WORK	-0.009 (0.020)	CO-OFC	0.078 (0.058)
N-BLACK	0.068 (0.083)	CF-SWORK	-0.427** (0.015)	CD-SEX	-0.129** (0.053)
A-BLACK	0.097* (0.059)	CF-CHILD	-0.023 (0.026)	CD-AGE	-0.015 (0.018)
A-ADBED	0.128** (0.041)	CF-OMC	-0.295** (0.028)	CD-AGE0	-0.149** (0.041)
A-ADBTH	0.031 (0.028)	CF-OFC	-0.085** (0.040)	CD-MARRY	0.187** (0.065)

Table 2 cont'd.

A-ADDRS	-0.095 (0.060)	CO-FEMALE	0.547** (0.043)	CD-MNDIST	0.060** (0.027)
A-ADEAT	0.209** (0.039)	CO-AGE/10	-0.046 (0.031)	CD-MXDIST	-0.013 (0.024)
A-ADTLT	-0.486** (0.096)	CO-MARRY	0.021 (0.035)	CD-WORK	-0.103** (0.048)

Notes:

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

2. Sample size is 1952.

3. N-variables are associated with nursing homes, A-variables are associated with living at home alone, CF-variables are associated with child effects for the family, CO-variables are associated with own child effects, and CD-variables are associated with child difference effects.

4. Most variables are defined in Table 1. Variables not defined in Table 1 are: OMC = dummy for oldest male child; OFC = dummy for oldest female child; CD-SEX = dummy if children i and j are opposite sex; CD-AGE, CD-MARRY, and CD-WORK are absolute value differences of age, marital status, and work status respectively between children i and j; AGEO = dummy if child j is older than child i; MNDIST = minimum possible distance between children i and j; MXDIST = maximum possible distance between children i and j.

Table 3

Total Estimated Effects for Child Explanatory Variables

for Voluntary Model

	Family Size		
Variable	2	3	4
C-DIST1	-0.976** (0.126)	-0.849** (0.152)	-0.723** (0.194)
C-DIST2	-1.077** (0.052)	-1.287** (0.069)	-1.498** (0.087)
C-DIST3	-1.242** (0.123)	-1.715** (0.159)	-2.189** (0.197)
C-DIST4	-1.564** (0.115)	-2.135** (0.145)	-2.707** (0.179)
C-DIST5	-2.166** (0.522)	-2.262** (0.695)	-2.357** (0.899)
C-WORK	-0.111** (0.050)	-0.120* (0.066)	-0.129 (0.083)
C-SWORK	0.109** (0.049)	-0.318** (0.059)	-0.744** (0.070)
C-CHILD	0.025 (0.055)	0.001 (0.080)	-0.022 (0.106)
C-OMC	0.313** (0.078)	0.018 (0.098)	-0.277** (0.122)
C-OFC	-0.092 (0.094)	-0.177 (0.128)	-0.262 (0.165)

Notes:

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

2. Sample size is 1952.

3. Variables are defined as weighted sums of variables from Table 2. For example, the effect of C-DIST4 is CO-DIST4 + (N*CF-DIST4) where N is the family size.

Table 4

Parameter Estimates for Collective Model

Variable	Estimate	Variable	Estimate	Variable	Estimate
N-CONSTANT	-1.249** (0.033)	A-ADWKI	0.000 (0.027)	CO-DIST1	-0.488** (0.102)
A-CONSTANT	0.421** (0.025)	N-PROGRAM	-0.038 (0.042)	CO-DIST2	-0.472** (0.078)
N-FEMALE	-0.076 (0.070)	N-RESLIM/10	0.060** (0.028)	CO-DIST3	-0.755** (0.191)
A-FEMALE	-0.042** (0.016)	N-INCLIM	0.028 (0.067)	CO-DIST4	-0.983** (0.167)
N-AGE/10	0.089** (0.020)	CF-DIST1	0.010 (0.029)	CO-DIST5	-2.116** (0.474)
A-AGE/10	-0.069** (0.011)	CF-DIST2	-0.052** (0.022)	CO-WORK	0.017 (0.045)
N-EDUC	0.005* (0.003)	CF-DIST3	-0.030 (0.077)	CO-SWORK	0.142** (0.053)
A-EDUC	0.004** (0.002)	CF-DIST4	-0.007 (0.034)	CO-CHILD	-0.017 (0.035)
N-MARRY	0.014 (0.062)	CF-DIST5	0.225 (0.137)	CO-OMC	0.316** (0.076)
A-MARRY	0.103** (0.022)	CF-WORK	-0.024 (0.023)	CO-OFC	-0.123* (0.069)
N-BLACK	-0.327 (0.271)	CF-SWORK	-0.070** (0.015)	CD-SEX	0.020 (0.055)
A-BLACK	0.075 (0.121)	CF-CHILD	0.010 (0.015)	CD-AGE	-0.048 (0.041)
A-ADBED	1.618** (0.154)	CF-OMC	-0.067** (0.022)	CD-AGE0	-0.032 (0.061)
A-ADBTH	0.072 (0.048)	CF-OFC	0.002 (0.023)	CD-MARRY	0.033 (0.132)

Table 4 cont'd

A-ADDRS	-0.169** (0.081)	CO-FEMALE	0.394** (0.050)	CD-MNDIST	0.034** (0.009)
A-ADEAT	0.544** (0.219)	CO-AGE/10	-0.026** (0.011)	CD-MXDIST	-0.026** (0.008)
A-ADTLT	-2.064** (0.116)	CO-MARRY	0.011 (0.039)	CD-WORK	-0.006 (0.094)

Notes:

1. Single starred items are significant at the 10% level, and double starred items are significant at the 5% level.

2. Sample size is 1952.

3. Variables are defined in Table 2.

Table 5

Total Estimated Effects for Child Explanatory Variables

for Collective Model

	Family Size		
Variable	2	3	4
C-DIST1	-0.467**	-0.457**	-0.446**
	(0.105)	(0.118)	(0.137)
C-DIST2	-0.575**	-0.627**	-0.678**
	(0.072)	(0.078)	(0.089)
C-DIST3	-0.814**	-0.844**	-0.873**
	(0.216)	(0.263)	(0.323)
C-DIST4	-0.997**	-1.004**	-1.011**
	(0.155)	(0.160)	(0.171)
C-DIST5	-1.666**	-1.440**	-1.215**
	(0.401)	(0.431)	(0.498)
C-WORK	-0.031	-0.054	-0.078
	(0.046)	(0.062)	(0.082)
C-SWORK	0.002	-0.068	-0.138*
	(0.062)	(0.071)	(0.082)
C-CHILD	0.002	0.012	0.022
	(0.035)	(0.044)	(0.055)
C-OMC	0.183**	0.116	0.049
	(0.077)	(0.087)	(0.101)
C-OFC	-0.119**	-0.118	-0.116
	(0.064)	(0.073)	(0.087)

Notes:

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

2. Sample size is 1952.

3. Variables are defined as weighted sums of variables from Table 2. For example, the effect of C-DIST4 is CO-DIST4 + (N*CF-DIST4) where N is the family size.

Table 6

Quadratic Forms in Residuals of the Two Models

	Uncensored	Censored
Collective Covariance Matrix		
Collective Residuals	0.119e+19	3900.8
Voluntary Residuals	0.112e+19	4917.62
Voluntary Covariance Matrix		
Collective Residuals	16790.0	3481.4
Voluntary Residuals	16383.0	3168.4

Notes:

1. There are 4600 degrees of freedom.

2. All uncensored quadratic forms are significant, and no censored quadratic forms are significant if it is assumed they are distributed chi-squared with 4600 degrees of freedom.

Table 7

Quadratic Forms for Out-of-SampleTests

	Uncensored	Censored
Observations with Questionable Imputed Variables		
Collective Covariance Matrix		
Collective Residuals	5296.3	126.2
Voluntary Residuals	0.2918e+9	136.9
Voluntary Covariance Matrix		
Collective Residuals	261.4	130.2
Voluntary Residuals	255.0	130.7

Notes:

1. There are 127 degrees of freedom.
2. All uncensored quadratic forms are significant, and no censored quadratic forms are significant if it is assumed they are distributed chi-squared with 127 degrees of freedom.

Observations with Parent Not Living Alone in the First Year		
Collective Covariance Matrix		
Collective Residuals	0.1443e+18	3128.5
Voluntary Residuals	0.7146e+17	3968.4
Voluntary Covariance Matrix		
Collective Residuals	6562.2	2683.7
Voluntary Residuals	6237.5	2464.9

Notes:

1. There are 2335 degrees of freedom.
2. All quadratic forms are significant except for censored voluntary residuals with the voluntary covariance matrix if it is assumed they are distributed chi-squared with 2335 degrees of freedom.

Table 8

Distribution of Side Payments

Race	Sex	Family Size	Number of Families	No Side Payments	Some Side Payments
WHITE	M	1	183	183	0
WHITE	M	2	133	133	0
WHITE	M	>2	364	306	58
WHITE	F	1	407	407	0
WHITE	F	2	222	217	5
WHITE	F	>2	451	347	104
BLACK	M	1	37	37	0
BLACK	M	2	9	9	0
BLACK	M	>2	18	18	0
BLACK	F	1	69	69	0
BLACK	F	2	33	33	0
BLACK	F	>2	26	20	6
TOTAL			1952	1779	173

Notes:

1. Race is either WHITE or BLACK. Sex is either male (M) or female (F). Family size is either 1, 2, or greater than 2.

Table 9

Chi-Square Goodness-of-Fit Statistics for Voluntary Model

Race	Sex	Family Size	Decile	Uncorrected GOF Stat	Corrected GOF Stat	Mean Residual	Observations
WHITE	M	S	.5-.6	13.393*	11.987*	-0.527	12
WHITE	M	S	.6-.7	7.754*	7.487*	-0.659	4
WHITE	M	S	.8-.9	5.230*	5.205*	-0.839	1
WHITE	M	B	.1-.2	0.193	0.189	0.039	16
WHITE	M	B	.2-.3	0.024	0.023	0.013	27
WHITE	M	B	.3-.4	0.023	0.022	0.025	8
WHITE	M	B	.4-.5	1.790	1.520	-0.221	9
WHITE	M	B	.5-.6	0.029	0.028	0.018	23
WHITE	M	B	.6-.7	3.432	2.033	-0.339	7
WHITE	M	B	.7-.8	1.316	1.268	-0.186	7
WHITE	M	B	.8-.9	15.472*	12.051*	-0.550	7
WHITE	M	B	.9-1.0	78.262*	62.057*	-0.643	10
WHITE	F	S	.5-.6	37.530*	26.516*	-0.515	35
WHITE	F	S	.6-.7	18.607*	16.332*	-0.570	13
WHITE	F	S	.7-.8	27.519*	25.061*	-0.660	12
WHITE	F	S	.8-.9	2.111	2.089	-0.358	2
WHITE	F	B	.1-.2	2.002	1.971	0.119	16
WHITE	F	B	.2-.3	0.065	0.057	-0.015	58
WHITE	F	B	.3-.4	0.245	0.242	-0.051	22
WHITE	F	B	.4-.5	0.014	0.012	-0.015	16
WHITE	F	B	.5-.6	6.393*	4.833*	-0.204	38
WHITE	F	B	.6-.7	7.652*	4.853*	-0.236	31
WHITE	F	B	.7-.8	16.761*	11.204*	-0.470	14
WHITE	F	B	.8-.9	5.081*	3.760	-0.178	19
WHITE	F	B	.9-1.0	28.114*	27.438*	-0.679	4
BLACK	M	S	.7-.8	2.800	2.776	-0.737	1
BLACK	M	B	.2-.3	1.052	1.047	-0.259	3
BLACK	M	B	.5-.6	1.104	1.101	-0.525	1
BLACK	F	S	.5-.6	5.707*	5.241*	-0.533	5
BLACK	F	S	.6-.7	3.691	3.599	-0.647	2
BLACK	F	S	.7-.8	3.577	3.518	-0.782	1
BLACK	F	S	.8-.9	5.932*	5.863*	-0.856	1
BLACK	F	B	.2-.3	0.578	0.564	0.148	5
BLACK	F	B	.3-.4	0.150	0.149	0.132	2
BLACK	F	B	.4-.5	0.017	0.070	0.046	2
BLACK	F	B	.5-.6	1.342	1.338	-0.573	1
BLACK	F	B	.6-.7	1.683	1.655	-0.627	1
BLACK	F	B	.7-.8	0.327	0.362	0.247	1
BLACK	F	B	.8-.9	0.159	0.159	0.138	1
Overall				307.13*	255.68*	-0.321	438
Standardized (39 df)				30.36*	24.53*		

Notes:

1. Starred items are significant at the 5% level.

2. Race is either WHITE or BLACK. Sex is either Male (M) or female (F). Family size is either small (S) (2) or big (B) (3 or more).

3. Observations for the first decile are deleted because of poor statistical properties. There are 881 observations in the first decile. Other cells are missing because they are empty.

4. Uncorrected GOF statistics ignore the variance of the parameter estimates. Corrected GOF statistics include it using equations (4.14) and (4.15).

5. Overall statistics have a χ^2_{36} distribution. The standardized statistics are distributed standard normal.

Table 10

Corrected Chi-Squared Goodness-of-Fit Statistics

for Voluntary Model by Decile

Decile	Corrected GOF Stat	DF	Standardized	Mean Residual	Observations
.1-.2	2.16	2	0.08	0.079	32
.2-.3	1.69	4	-0.82	-0.006	93
.3-.4	0.41	3	-1.06	-0.021	32
.4-.5	1.60	3	-0.57	-0.079	27
.5-.6	51.04	7	11.77	-0.308	115
.6-.7	35.96	6	8.65	-0.373	58
.7-.8	44.19	6	11.02	-0.474	36
.8-.9	29.14	6	6.68	-0.307	31
.9-1.0	89.50	2	43.75	-0.653	14

Table 11

1984 Baseline Population Characteristics

Explanatory Variables					
Parents			Children		
Variable	Mean	Std. Dev.	Variable	Mean	Std. Dev.
AGE	80.16	7.02	AGE	52.22	8.13
FEMALE	0.56	0.50	FEMALE	0.52	0.50
BLACK	0.08	0.26	MARRY	0.75	0.43
MARRY	0.53	0.50	DIST1	0.17	0.37
EDUC	10.57	3.67	DIST2	0.20	0.40
No. ADL's	0.29	0.43	DIST3	0.11	0.31
No. Children	1.49	1.25	DIST4	0.34	0.47
			DIST5	0.15	0.35
			WORK	0.72	0.45
			SWORK	0.55	0.50
Living Arrangements					
	Popul. Prob.	Live w/ Spouse	Live Alone	Nursing Home	Children
By Age					
70-74	0.26	0.626	0.305	0.039	0.031
75-79	0.28	0.563	0.343	0.049	0.044
80-84	0.21	0.451	0.405	0.069	0.075
85-89	0.13	0.336	0.443	0.091	0.130
90-94	0.07	0.220	0.451	0.118	0.211
95-99	0.05	0.116	0.427	0.161	0.296
By Sex					
MALE	0.44	0.662	0.226	0.062	0.050
FEMALE	0.56	0.336	0.485	0.070	0.108
By Race					
WHITE	0.92	0.489	0.358	0.068	0.084
BLACK	0.08	0.361	0.526	0.047	0.066
By Marital Status					
MARRY	0.53	0.913	0.000	0.043	0.044
NOT MARRY	0.47	0.000	0.782	0.093	0.125
Total	1.00	0.480	0.371	0.067	0.083

Notes:

1. Variables are defined in Table 1.

2. "Popul. Prob." is the proportion of the population in the relevant group.

3. One million families were simulated. 933074 families had 4 or fewer children the first year. Of those, 852657 of the elderly family members survived to the second year.

Table 12

Effect of Reducing Family Size

Changes in Living Arrangement Probabilities					
	Popul. Prob.	Live w/ Spouse	Live Alone	Nursing Home	Children
By Age					
70-74	0.26	0.005	0.000	0.001	-0.006
75-79	0.28	0.006	0.002	0.002	-0.010
80-84	0.21	0.003	0.010	0.003	-0.016
85-89	0.13	0.006	0.014	0.005	-0.025
90-94	0.07	0.006	0.019	0.009	-0.034
95-99	0.05	0.006	0.025	0.017	-0.048
Total	1.00	0.005	0.007	0.003	-0.016
Elasticity in Living Arrangement Probabilities					
	Popul Prob.	Live w/ Spouse	Live Alone	Nursing Home	Children
By Age					
70-74	0.26	0.042	0.008	0.098	-1.062
75-79	0.28	0.055	0.036	0.167	-1.160
80-84	0.21	0.036	0.124	0.235	-1.102
85-89	0.13	0.088	0.164	0.287	-0.993
90-94	0.07	0.147	0.217	0.387	-0.834
95-99	0.05	0.264	0.300	0.534	-0.827
Total	1.00	0.069	0.090	0.213	-1.061

Notes:

1. Average family size is reduced by .29 by deflating the uniform random variable determining family size by 20%.

2. “Popul. Prob.” is the proportion of the population in the relevant group.

3. Elasticities are derivatives of log probabilities with respect to log number of children.

4. One million families were simulated. All families had 4 or fewer children the first year. Of those, 913767 of the elderly family members survived to the second year.

Table 13

Effect of Children Moving Intermediate Distances Away

Changes in Living Arrangement Probabilities					
	Popul. Prob.	Live w/ Spouse	Live Alone	Nursing Home	Children
By Age					
70-74	0.26	0.005	0.003	0.000	-0.008
75-79	0.28	0.006	0.004	0.000	-0.010
80-84	0.21	0.007	0.007	0.000	-0.014
85-89	0.13	0.008	0.011	0.001	-0.020
90-94	0.07	0.008	0.015	0.002	-0.025
95-99	0.05	0.005	0.015	0.003	-0.023
Total	1.00	0.006	0.007	0.001	-0.014

Notes:

1. The distance distribution is altered so that Pr(DIST0) decreases 3%, Pr(DIST1) decreases by 9%, Pr(DIST2) increases by 8%, and Pr(DIST3) increases by 4%.

2. "Popul. Prob." is the proportion of the population in the relevant group.

3. One million families were simulated. 933074 families had 4 or fewer children the first year. Of those, 852657 of the elderly family members survived to the second year.

Table 14

Effect of Decreasing Death Probabilities

Changes in Living Arrangement Probabilities					
	Popul. Prob.	Live w/ Spouse	Live Alone	Nursing Home	Children
By Age					
70-74	0.26	0.003	-0.003	-0.000	-0.000
75-79	0.28	0.003	-0.003	-0.000	-0.000
80-84	0.21	0.001	-0.001	0.000	0.000
85-89	0.13	0.006	-0.006	-0.001	-0.000
90-94	0.07	0.007	-0.006	-0.001	-0.000
95-99	0.05	0.003	-0.006	-0.002	0.005

Notes:

1. Death probabilities are reduced 50% (conditional on the original 1982 joint density of age, sex, and race). This increases the average age of the parent by 0.04, the average age of the children by 0.06, the number of living children by 0.004, the proportion of female children by 0.04, and the proportion of children married by 0.005.

2. "Popul. Prob." is the proportion of the population in the relevant group.

3. One million families were simulated. 909835 families had 4 or fewer children the first year. Of those, 848235 of the elderly family members survived to the second year.

Table 15

Effect of Changing Medicaid Resource Limit

Changes in Living Arrangement Probabilities					
	Popul. Prob.	Live w/ Spouse	Live Alone	Nursing Home	Children
By Age					
70-74	0.26	-0.005	-0.004	0.009	-0.000
75-79	0.28	-0.005	-0.006	0.011	-0.000
80-84	0.21	-0.006	-0.009	0.015	-0.001
85-89	0.13	-0.005	-0.012	0.019	-0.001
90-94	0.07	-0.004	-0.016	0.023	-0.003
95-99	0.05	-0.003	-0.021	0.029	-0.005
Total		-0.005	-0.008	0.014	-0.001

Notes:

1. The resource limit is doubled. Thus the reported numbers are also elasticities.

2. "Popul. Prob." is the proportion of the population in the relevant group.

3. One million families were simulated. 933074 families had 4 or fewer children the first year.

   Of those, 852657 of the elderly family members survived to the second year.

Table 16

Family Welfare Comparisons

Family Size	1	2	3	4	5
Split-the-Rents Side-Payment Rule					
Parent Utility	-0.535 (0.223)	-0.400 (0.202)	-0.365 (0.186)	-0.326 (0.167)	-0.301 (0.151)
Child Mean Utility		-0.374 (0.216)	-0.371 (0.192)	-0.334 (0.177)	-0.312 (0.162)
Child Std. Dev. Utility			0.035 (0.040)	0.038 (0.047)	0.042 (0.041)
Mean Side payment		0.020 (0.081)	0.003 (0.029)	0.000 (0.020)	-0.001 (0.013)
Social Planner's Side-Payment Rule					
Parent Utility	-0.535 (0.223)	-0.408 (0.220)	-0.386 (0.217)	-0.357 (0.204)	-0.350 (0.190)
Child Mean Utility		-0.347 (0.321)	-0.344 (0.214)	-0.308 (0.194)	-0.282 (0.173)
Child Std. Dev. Utility			0.119 (0.147)	0.115 (0.141)	0.131 (0.128)
Mean Side Payment		0.005 (0.140)	-0.012 (0.073)	-0.014 (0.051)	-0.017 (0.038)
Parent Utility-Maximizing Side-Payment Rule					
Parent Utility	-0.535 (0.223)	-0.224 (0.207)	-0.017 (0.188)	0.201 (0.167)	0.403 (0.166)
Child Mean Utility		-0.600 (0.215)	-0.585 (0.214)	-0.553 (0.204)	-0.538 (0.186)
Child Std. Dev. Utility			0.020 (0.026)	0.026 (0.037)	0.032 (0.035)
Mean Side Payment		0.208 (0.106)	0.192 (0.057)	0.189 (0.045)	0.187 (0.033)

Table 16 cont'd

Shapley Value Side-Payment Rule					
Parent Utility	-0.535 (0.223)	-0.393 (0.210)	-0.356 (0.217)	-0.329 (0.251)	-0.321 (0.288)
Child Mean Utility		-0.380 (0.212)	-0.374 (0.218)	-0.329 (0.217)	-0.300 (0.195)
Child Std. Dev. Utility			0.041 (0.053)	0.044 (0.057)	0.055 (0.061)
Mean Side Payment		0.026 (0.126)	0.008 (0.093)	-0.002 (0.089)	-0.008 (0.075)
No-Side-Payments Rule					
Parent Utility	-0.535 (0.223)	-0.425 (0.212)	-0.377 (0.199)	-0.333 (0.175)	-0.302 (0.153)
Child Mean		-0.339 (0.278)	-0.364 (0.196)	-0.332 (0.184)	-0.312 (0.169)
Child Std. Dev. Utility			0.060 (0.092)	0.064 (0.101)	0.073 (0.089)
Mean Side Payment		0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Number of Families	696	397	455	275	129

Notes:

1. Numbers in parentheses are standard deviations. To turn them into standard errors of the numbers above them, divide by the square root of the sample size in the last row.

2. Side payments are measured from children to parent.

3. Results are based on the parameter estimates from the voluntary model reported in Table 2.

Figure 2

Distribution of Voluntary Residuals by State

Nursing Home

f1*(7.29) al,ar,ct,il,mi,ne,pa,ri,va, wi,wy	mn*(48.88),ky*(19.80), ks,mo,oh,or,sc
	Home
de,dc,ga,id,la,nj,ut	tn*(1163.56),co*(27.77), ma*(7.99) ca,in,ia,me,md,ms,mt,nh,ny nc,nd,ok,tx,wa,wv

Notes:

1. Starred items have significant χ_2^2 statistics, and numbers next to them are the value of the test statistic.

2. State residuals are categorized by signs of average residuals.

3. The chi-squared statistic for the whole sample is 1308.33 with 86 degrees of freedom. If outliers are censored at the 0.001 significance level, the statistic becomes 90.72.

Density of Voluntary Residuals

By Family Size

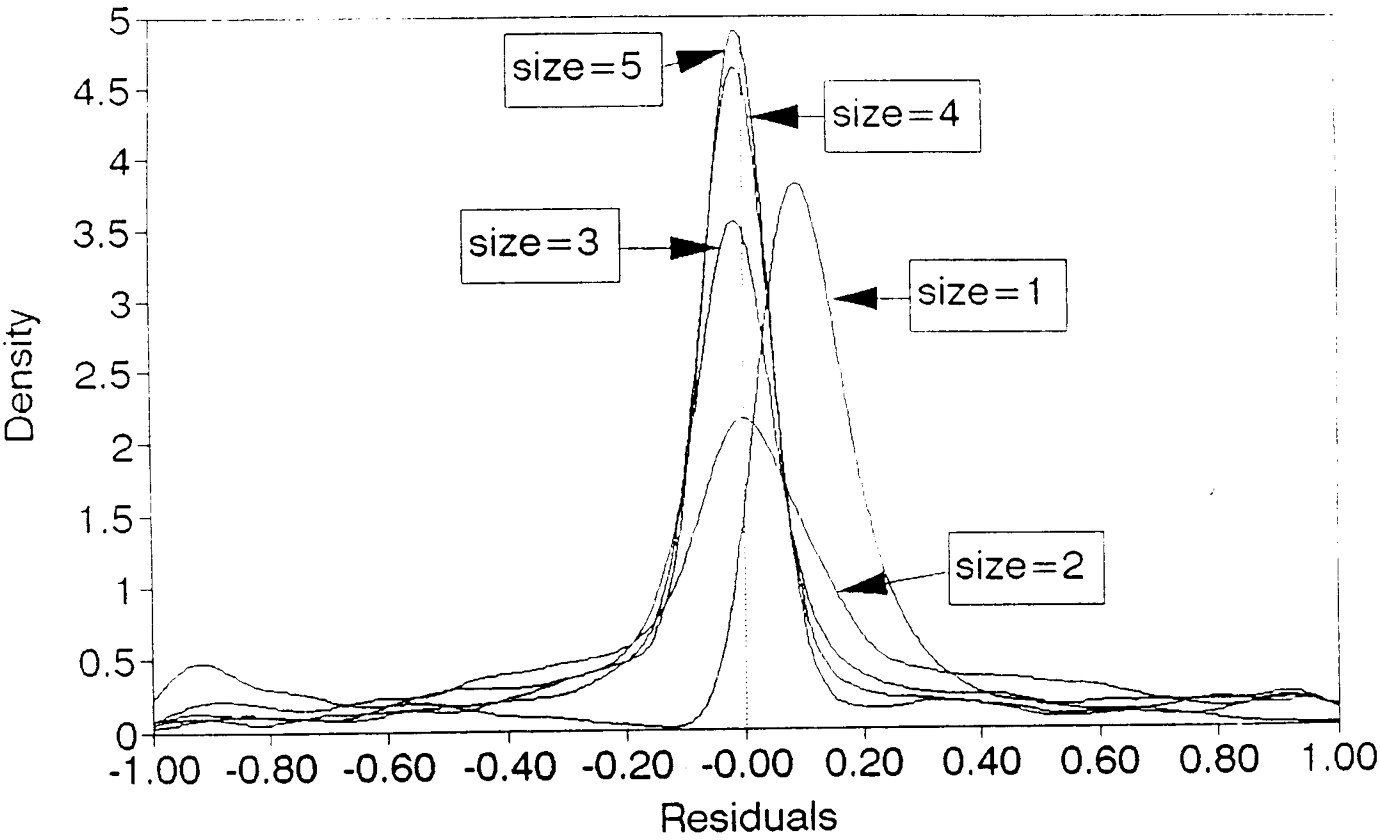


Figure 2

Distribution of Voluntary Residuals by State

Nursing Home

f1*(7.29) al,ar,ct,il,mi,ne,pa,ri,va, wi,wy	mn*(48.88),ky*(19.80), ks,mo,oh,or,sc
de,dc,ga,id,la,nj,ut	tn*(1163.56),co*(27.77), ma*(7.99) ca,in,ia,me,md,ms,mt,nh,ny nc,nd,ok,tx,wa,wv

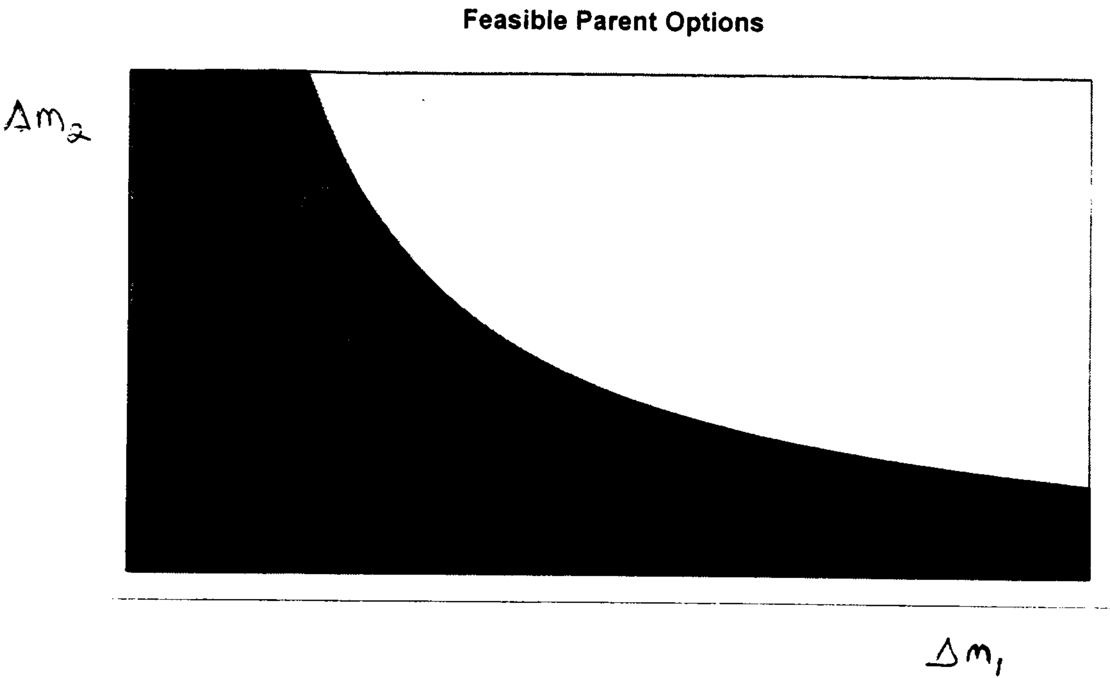
Home

Notes:

1. Starred items have significant χ^2_2 statistics, and numbers next to them are the value of the test statistic.

2. State residuals are categorized by signs of average residuals.

3. The chi-squared statistic for the whole sample is 1308.33 with 86 degrees of freedom. If outliers are censored at the 0.001 significance level, the statistic becomes 90.72.


Feasible Parent Options
Δm_2
Δm_1