Will You Still Want Me Tomorrow? The Dynamics of Families' Long-Term Care Arrangements

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Abstract

We estimate dynamic models of elder-care arrangements using data from the Assets and Health Dynamics Among the Oldest Old Survey. We model the use of institutional care, formal home health care, care provided by a child, and care provided by a spouse in the selection of each care arrangement, the primary arrangement, and hours in each arrangement. Our results indicate that both observed heterogeneity and true state dependence play roles in the persistence of care arrangements. We find that positive state dependence (i.e., inertia) dominates caregiver burnout, and that formal care decisions depend on the cost and quality of care.

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In light of population aging and high disability rates among elderly individuals (Butler, 1997; Spillman and Long, 2007), many families face decisions concerning long-term care arrangements for disabled elderly relatives. With the assistance of family members, most notably spouses and adult children, many disabled elderly individuals remain in the community (Shirey and Summer, 2000). Others rely exclusively on formal home health care or a combination of formal home health care and informal care provided by relatives and friends (Mack and Thompson, 2005). Institutional care represents the other major source of care for this population (Burwell and Jackson, 1994).

Long-term care arrangements have profound economic, social, and psychological implications. Komisar and Thompson (2007) report that national spending on long-term care for elderly and disabled individuals exceeded $200 billion in 2005. Medicaid and Medicare respectively covered approximately 49 and 20 percent of these expenses, while private health and long-term care insurance covered roughly 7 percent. Individuals and their families financed about 18 percent of long-term care services that year, while the remaining 5 percent was financed by other private and public sources (Komisar and Thompson, 2007). Most informal care provided by family members is unpaid, but the opportunity costs in terms of foregone earnings, household production, and leisure are often substantial. Moreover, the provision of informal care can be psychologically burdensome for caregivers (Martin, 2000; Byrne, et al., 2009, hereafter BGHS), and institutional care often entails high social and psychological costs for elderly individuals (Macken, 1986).

The aging of the population and the profound implications of care arrangements for elderly individuals, their families, and society highlight the importance of developing appropriate public policies concerning long-term care arrangements for the elderly. Although an extensive literature examines families' long-term care decisions, most studies neglect the intertemporal dimensions of care. Using data from five waves of the Assets and Health Dynamics Among the Oldest Old Survey collected between 1995 and 2004, we contribute to the long-term care literature by developing and estimating three dynamic models of families' elder care arrangements. These models distinguish among care provided by a spouse, care provided by an adult child or child-in-law, formal home health care, and institutional care, while also allowing for the possibility that the elderly individual remains independent. Our models capture several dimensions of families' care arrangements, namely the use of each potential care arrangement, the selection of the primary care arrangement, and hours in each potential care arrangement. Our dynamic framework links care arrangements over time by allowing for state dependence while distinguishing between spurious state dependence due to observed and unobserved heterogeneity and true state dependence (e.g., due to inertia or caregiver burnout). For example, our models distinguish between persistence in care arrangements attributable to a family's preferences (e.g., an aversion to institutional care) and true state dependence stemming from the high costs of transitioning from one care arrangement to another (e.g., into or out of institutional care). Our results suggest that inertia (i.e., positive true state dependence) contributes to persistence in long-term care arrangements, thus highlighting the importance of a framework that links care arrangements over time.

1 Literature Review

Although predominantly empirical, the long-term care literature offers several formal economic models. Given the complexities inherent in families' long-term decisions, none of these models captures all dimensions of decision-making within families. These models vary with respect to the assumptions concerning family members' preferences, the number of children participating in the decision-making process, and the scope of care decisions considered.

Allowing for the possibility that preferences vary across family members, several papers present game-theoretic models (Sloan, Picone and Hoerger, 1997, hereafter SPH; Hiedemann and Stern, 1999, hereafter HS; Pezzin and Schone, 1999a, hereafter PSa; Checkovich and Stern, 2002, hereafter CS; Engers and Stern, 2002, hereafter ES; Brown, 2006; Pezzin, Pollak and Schone, 2007, hereafter PPS; BGHS). Other models are based on the assumption of common preferences; for example, Hoerger, Picone, and Sloan (1996) and Stabile, Laporte, and Coyte (2006) rely on the assumption of a single family utility function. Kotlikoff and Morris (1990) model the parent and child solving separate maximization problems if they live separately but maximizing a weighted average of their individual utility functions subject to their pooled budget constraint if they live together. In contrast to our previous work (e.g., HS, ES, BGHS), this paper abstracts from the possibility that family members have different preferences concerning care arrangements in order to focus on the dynamic dimension of care.

Several models accommodate all adult children in the decision-making process (HS; CS; ES; Van Houtven and Norton, 2004; Brown, 2006; BGHS). Others simplify modeling and/or estimation by focusing on families that include only one child (Kotlikoff and Morris, 1990) or two adult children (PPS) or by assuming that only one child participates in the family's long-term care decisions (SPH, PSa). In this paper, we restrict our sample to families with at most four children, but we treat each child as a potential caregiver.

The models in this literature also vary with respect to the scope of care decisions examined. Models presented in HS and ES focus on the family's selection of the primary care arrangement including informal care provided by an adult child, institutional care, or continued independence. CS and Brown (2006) model the quantity of informal care provided by each adult child. Similarly, SPH, PSa, Stabile, Laporte, and Coyte (2006), and BGHS model the provision of informal care and formal home health care. Stabile, Laporte, and Coyte (2006) distinguish between publicly and privately financed home health care. Van Houtven and Norton (2004) model children's provision of informal care and parent's use of formal care, defined broadly as nursing home care, home health care, hospital care, physician visits, and outpatient surgery. Hoerger, Picone, and Sloan (1996) and PPS focus on living arrangements of sick or disabled elderly individuals (e.g., independent living in the community or residence in an intergenerational household). Distinguishing among care provided by a spouse, care provided by an adult child or child-in-law, formal home health care, and institutional care, this paper examines three dimensions of families' care arrangements: the use of each potential mode of care, the selection of the primary care arrangement, and hours in each arrangement.

Although the provision of elder care is an inherently dynamic process, most of the literature abstracts from the intertemporal dimensions of care. Exceptions include Börsch-Supan, Kotlikoff, and Morris (1991) (hereafter BKM), Garber and MaCurdy (1990) (hereafter GM), Dostie and Léger (2005) (hereafter DL), Heitmueller and Michaud (2006) (hereafter HM), and Gardner and Gilleskie (2009). Using a framework that accounts for unobserved heterogeneity and state dependence, HM explore the causal links between employment and informal care of sick, disabled, or elderly individuals over time. In a dynamic model of savings and Medicaid enrollment decisions, Gardner and Gilleskie (2009) jointly estimate long-term care arrangements, savings/gifting behavior, insurance coverage, and health transitions. Their approach incorporates unobserved permanent and time-varying heterogeneity.

The other studies focus on living arrangements of elderly individuals. BKM examine transitions among living independently, living with adult children, and living in an institution. GM model transitions from living in the community to residing in a nursing home and vice versa as well as transitions from one of these two living arrangements to death. Accounting for unobserved heterogeneity as well as state and duration dependence, DL examine transitions among independent living, cohabitation, nursing home residence, and death.

Following DL, HM, and Gardner and Gilleskie (2009), our models account for unobserved heterogeneity and state dependence. Distinguishing among care provided by a spouse, care provided by an adult child or child-in-law, formal home health care, and institutional care, our models encompass a broader range of care arrangements than those in the existing literature. Examining three care dimensions of elder care decisions – the use of each potential mode of care, the selection of the primary care arrangement, and hours in each arrangement, we also provide a richer description of long-term care dynamics.

2 Data

To examine families' care arrangements over time, we use data from the 1995, 1998, 2000, 2002, and 2004 waves of the Assets and Health Dynamics Among the Oldest Old (AHEAD)/ Health and Retirement (HRS) survey. With an emphasis on the joint dynamics of health and demographic characteristics, this nationally representative longitudinal survey provides a particularly rich source of information concerning long-term care arrangements. Selection criteria for the initial AHEAD/HRS survey, conducted in 1993, include age and living arrangements. In particular, this initial wave contains 6047 households with non-institutionalized individuals aged 70 years or older. However, subsequent waves retain all living respondents, thus enabling the study of elderly individuals in the community as well as nursing home residents. Spouses of respondents are also respondents even if they would not otherwise qualify on the basis of their own age, thus increasing the sample size for the initial wave to 8222 respondents. Although AHEAD/HRS oversamples Florida residents, this oversampling introduces no estimation bias assuming that residential location is exogenous. AHEAD/HRS also oversamples black and Hispanic households.

After excluding observations with missing values for variables used in our analysis, individuals who participated in only one wave of the survey, individuals who provided inconsistent responses, individuals who married or remarried over the course of the survey, families with more than four children, and mixed-race couples, our sample consists of 3353 individuals including spouses of original respondents. In addition to 914 married couples (where each individual represents a respondent), the sample includes 267 unmarried men and 1258 unmarried women. The preponderance of women (nearly two thirds of the sample) and the higher marriage rates among men (77.4 percent of men compared to 42.1 percent of women) reflect differences in life expectancy by gender and age differences between husbands and wives. Fifty-three percent of elderly households participate in all five waves of the survey.

Our models include characteristics that influence an elderly individual's caregiving needs, opportunities, and preferences. The need for care may increase with age and activity limitations; accordingly, our models control for the elderly individual's age, problems with activities of daily living (ADLs), and problems with instrumental activities of daily living (IADLs). The presence of a spouse may reduce an elderly individual's need for assistance from adult children or from formal care providers, particularly if the spouse is relatively young and healthy; thus, our models control for the elderly individual's marital status, the spouse's age, and the spouse's activity limitations. Since patterns of care may differ for men and women and across white, black, and Hispanic families, our models control for gender as well as race/ethnicity. Moreover, to capture potential differences in care arrangements for mothers/wives relative to fathers/husbands by race and ethnicity (see Goeree, Hiedemann, and Stern, 2010), one of our discrete choice models also includes interactions between gender and race/ethnicity.

Assets are potentially important characteristics that influence an elderly individual's caregiving needs and opportunities in that the ability to purchase care may reduce an individual's dependence on relatives. Unfortunately, there are several problems with the asset data reported in AHEAD. The first problem concerns large, spurious changes in assets within families across time due to changes in the survey structure (for details, see Hurd, Juster, and Smith, 2003 and Juster et al., 2007). Since transitions are very important in a dynamic model, the large variation in asset changes is problematic. Hill (2006) also finds unreasonable variation in changes in assets in HRS.[2] Second, among wealthier individuals, 1993 assets are understated by a factor of two. Third, income and asset reports in the second wave are inconsistent. Fourth, mean assets double between the second and third waves. Fifth, financial measures, particularly those related to equity in a second home, are under-reported (Hurd, Juster, and Smith, 2003; Juster et al., 2007). Finally, income measures are under-reported or mis-reported (Hurd, Juster, and Smith, 2003). In the absence of good asset and income data, our models include the elderly individual's educational attainment as a proxy for her financial resources. We test whether assets, as measured in AHEAD/HRS, affect family decisions and explore how best to use the data by conducting Lagrange Multiplier tests.

Table 1 displays descriptive statistics for the respondents for the first year of data.[3] As a consequence of the exclusion of nursing home residents from the initial wave and the inclusion of spouses regardless of age, the characteristics of our sample differ from those of a random sample of individuals aged 72 years and over.[4] Respondents range from 49 to 103 years with a mean of 78 years and a standard deviation of 6 years. On average, the respondents report difficulty with 0.54 activities of daily living (ADL) such as eating, dressing, or bathing. But the sample displays considerable variation with regard to ADL problems; while some individuals report no problems with activities of daily living, others report problems with as many as six ADLs. Similarly, the respondents report an average of 0.43 problems with instrumental activities of daily living (IADLs), such as using a telephone, taking medication, handling money, shopping, or preparing meals; here too the sample displays considerable variation, with respondents reporting a range of zero to five IADL problems. In addition

[2] He performs an experiment with later waves of HRS where respondents are told how they answered the asset questions in the last wave; this results in a significant reduction in the variance of asset changes.

[3] For most respondents, the first year of data used in our analysis is 1995; for some, it is later.

[4] The AHEAD data surveys respondents aged 70 or older in the first wave from 1993. Our data starts with the second wave in 1995.

to 2906 individuals (86.7 percent of the sample) who identify as non-Hispanic white, the sample includes 324 individuals (9.7 percent of the sample) who identify as non-Hispanic black and 123 individuals (3.7 percent of the sample) who identify as Hispanic. Although the original sample includes individuals with other racial/ethnic identities, none of these individuals remained in the sample after applying the selection criteria. With respect to education, 33.2 percent of respondents have a high school diploma but not a college degree, and 31.0 percent report having a college or graduate degree.

Variable	Mean	Std Dev	Min	Max
Characteristics of Elderly Respondents (N=3353)				
Female	0.65	0.48	0	1
Black	0.10	0.30	0	1
Hispanic	0.04	0.19	0	1
Age	77.96	6.03	49	103
Married	0.55	0.50	0	1
High School Diploma	0.33	0.47	0	1
College Degree	0.31	0.46	0	1
# ADL Problems	0.54	1.25	0	6
# IADL Problems	0.43	1.06	0	5
Characteristics of Adult Children and Children-in-Law (N=7807)				
Female	0.51	0.50	0	1
Age	48.86	8.42	14	89
Married	0.85	0.36	0	1
Number of Children	2.18	1.57	0	13
Years of Education	13.94	2.36	0	18
Weekly Hours of Work	29.77	16.33	0	40
Resides within 10 Miles of Parent	0.36	0.48	0	1
Resides with Parent	0.03	0.18	0	1
Market Conditions (N=2439)				
Home Health Care Per Week ($100)	8.72	0.73	6.99	10.81
Ln (Nursing Home Beds Per Individual Above 70 Years)	-2.85	0.38	-3.64	-2.27
Average ADL Score	5.81	0.31	5.20	6.70
Nursing Home Staff Hours Per Resident Per Day	3.06	0.23	2.40	3.60
Medicaid Policies Facing Households in Our Sample in 1993				
Medically Needy Program (N = 2439)	0.96	0.20	0	1
Income Limit Facing Individuals (N = 1525)	446	79	238	724
Income Limit Facing Couples (N = 914)	673	160	311	1110

Table 1: Descriptive Statistics

The elderly households in our sample report a total of 4489 adult children and 3318 children-in-law. Since each member of this generation is a potential caregiver, our models include demographic characteristics of the adult children and children-in-law. These characteristics reflect a potential caregiver's opportunity costs of time, effectiveness in the caregiving role, and/or caregiving burden. Specifically, the models control for the adult child's or child-in-law's years of schooling, work status, marital status, family size (number of children), age, and gender. As discussed extensively in Goeree, Hiedemann, and Stern (2010), the role of child gender in elder care provision may vary by race and ethnicity; thus, one of our models also interacts child gender with race and ethnicity. Finally, co-residence with or proximity to an elderly parent or parent-in-law may facilitate care provision. As discussed in Rainer and Seidler (2009), location may be endogenous. However, Stern (1995) shows that, even after controlling for endogeneity, geographical distance explains variation in informal care arrangements. Accordingly our models include measures of distance and co-residence, and we conduct likelihood ratio tests to infer whether location is endogenous.

As shown in the second panel of Table 1, the younger generation displays near gender balance: 51.1 percent are daughters or daughters-in-law. The average child or child-in-law is almost 49 years old with nearly 14 years of schooling. These individuals report 29.8 hours of labor market work per week, but this figure understates mean labor market activity because weekly work hours are truncated at 40.0. On average, the adult children and children-in-law of the elderly respondents have 2.2 children, but it is worth noting that some of these children belong to both a child and a child-in-law. A small proportion (3.3 percent) of the adult children and children-in-law reside with the elderly respondents, and 35.5 percent lives within 10 miles of the elderly respondents.

In addition to demographic characteristics and activity limitations, market conditions and public policies may influence families' care arrangements for elderly individuals. Our models control for several dimensions of the market for formal care in the elderly individual's or couple's state of residence: the average weekly cost of full-time home health care (16 hours a day for seven days or 112 hours per week), nursing home staff hours per nursing home resident per day in facilities with Medicare or Medicaid beds, nursing home beds per individual above 70 years, and a measure of the overall level of disability among nursing home residents. As discussed in Harrington, Carrillo and LaCava (2006), this disability measure (Average ADL Score) is a composite score that reflects nursing home residents' needs for assistance with three ADLs, namely eating, toileting, and transferring. Each nursing home resident was assigned a score from one to three for each of these ADLs, increasing in the amount of assistance needed. A summary score ranging from three to nine was compiled for each facility; facility scores were then summarized for each state.[5]

The market for formal home health care and institutional care varies by state. The statistics presented in the third panel describe the market conditions facing elderly households in our sample during the first year of data. On average, these households reside in states where the mean weekly cost of full-time home health care is $872. Ranging from $699 to $1081, these are real costs, deflated with state-specific price deflators (Bureau of Economic Analysis, 1999). The elderly households in our sample live in states with 2.4 to 3.6 nursing home staff hours per nursing home resident per day and 2.6 ($100 * \exp(-3.637)$) to 10.3 beds per 100 individuals over 70 years. On average, these households reside in states where the facility score ranges from 5.2 to 6.7, with a mean of 5.8 and a standard deviation of 0.31.

Many households rely on public assistance, most notably Medicaid, to cover their long-term care expenses. Eligibility for Medicaid is linked to actual or potential receipt of cash assistance under the Supplemental Security Income (SSI) program or the former Aid to Families with Dependent Children program. Elderly individuals or couples are eligible for SSI payments if their monthly countable income (income less $20) and countable resources fall below a certain threshold. Income limits for Medicaid eligibility vary widely by state; given the lack of state-level data for some years and the high correlation of a state's income limits across time, our models include only 1993 income limits.[6] In most states, individuals or couples whose incomes exceed the limits for Medicaid eligibility qualify for assistance if their medical expenses are high relative to their incomes. In the presence of a medically needy program, households may deduct medical expenses from income when determining eligibility for Medicaid coverage of nursing home care or formal home health care. Thus, our models also control for the presence of a medically needy program.

The bottom panel of Table 1 presents the 1993 average Medicaid income limits facing elderly individuals in our sample as well as the proportion of sampled households residing in states with a medically needy program. Individuals face monthly income limits ranging from $238 to $724 with a mean of $446; couples face monthly income limits ranging from

[5] Wages for home health aide workers were obtained from PHI (2007). The nursing home data were obtained from Grabowski et al. (2004) and Harrington, Carrillo and LaCava (2006).

[6] See http://www.people.virginia.edu/~sns5r/resint/ltcstf/medicaideligibility.pdf

$311 to $1110 with a mean of $673. Over 95 percent of the households in our sample reside in states that had a medically needy program in 1993.

As discussed in more detail later, we present three dynamic models of families' long-term care decisions. In particular, we model the family's decision whether to use each potential care arrangement (section 3.1), the family's selection of the primary care arrangement (section 3.3), and hours spent in each care arrangement (section 3.5). Our models distinguish among several modes of care – institutional care, formal home health care, informal care provided by a spouse, and informal care provided by a child or child-in-law – while allowing for the possibility that an elderly individual does not receive any of these modes of care.

Mode of Care	Informal Care By Spouse	Informal Care By Child or Child-in-Law	Formal Home Health Care	Institutional Care
Any of this Mode (All Respondents)	6.7%	3.2%	1.3%	0.1%
Primary Arrangement (All Respondents)	6.7%	1.5%	0.7%	0.1%
Primary Arrangement (Care Recipients Only)	74.7%	16.6%	8.0%	1.0%
Mean Weekly Hours (Recipients of this Mode of Care)	56	7	13	93

Table 2: Frequency of Care Mode

Ninety-one percent of the elderly individuals in our sample receive no care during the first year. Among those relying on at least one mode of care, informal care arrangements are more common than formal care arrangements. More specifically, as shown in Table 2, 6.7 percent of respondents receive care from a spouse, and 3.2 percent receive care from an adult child or child-in-law. While 1.3 percent of respondents rely on formal home health care, only 0.1 percent receives nursing home care. Similarly, informal care arrangements are more common than formal arrangements as the primary mode of care.

Not surprisingly, institutionalized elderly individuals receive more care than do elderly care recipients who remain in the community. As shown in Table 2, the average nursing home resident receives 93 hours of care per week in the first year of data. Also, spousal caregivers tend to provide substantially more care than do formal home health care providers or adult children. On average, during the first year of data, spousal caregivers provide 56 hours of care per week. In contrast, the average amount of formal home health care is 13 hours per week among those who rely on this mode of care. The comparable figure for care provided by adult children or children-in-law is seven hours per week.

As discussed earlier, we observe each elderly individual in our sample for at least two and at most five different time periods. Corresponding to 73816 possible transitions into and out of each potential care arrangement, Table 3 shows the number of observed transitions. We observe 401 transitions into spousal care (a transition rate of over ten percent) and 254 transitions out of spousal care (a transition rate of over 46 percent). Transition rates into non-spousal care arrangements range from just over one percent (child or child-in-law) to just under one percent (institutional care). We observe a transition rate out of care by a particular child or child-in-law care of almost 43 percent, a rate of over 67 percent out of formal home care, and a rate of 26 percent out of institutional care.

	Persistence in Care Arrangements Across Two Consecutive Waves		Transitions Into and Out of Care Arrangements	
Care Arrangement	Used Neither Period	Used Both Periods	Not Used/Used	Used/Not Used
Spouse	3451	289	401	254
Child or Child-in-Law	26628	197	362	146
Formal Home Health Care	9025	33	101	68
Institutional Care	9120	20	80	7

Notes: These figures condition on the availability of the potential care arrangement in the first period of the transition in question. Spouses and children are considered available as long as they are alive.

Table 3: Intertemporal Patterns of Care

3 Dynamic Models of Long-Term Care Arrangements

We model three related dimensions of families' care arrangements for an elderly individual in a particular time period: the use of each potential care arrangement, the selection of the primary care arrangement, and hours spent in each care arrangement. Our models distinguish among several modes of care: institutional care, formal home health care, informal care provided by the spouse, and informal care provided by an adult child or child-in-law. Our models also allow for the possibility that the elderly individual receives no formal or informal care in a particular period. In each model, the family makes decisions taking into account characteristics of the potential care arrangements. In contrast to our previous work (e.g., HS; ES; BGHS), we abstract from the possibility that family members have different preferences concerning care and from details about how the family makes decisions.

Care arrangements may persist as a result of the family's preferences or constraints or as a result of inertia. For example, a family's aversion to institutional care may lead to persistence in care arrangements. Differences across family members with respect to their caregiving effectiveness or their opportunity costs of time may also contribute to persistence in care arrangements. Accordingly, our models control for observable factors as well as several types of unobserved heterogeneity that may lead to persistence in care arrangements (i.e., spurious state dependence). Moreover, the costs of transitioning from one care arrangement to another may enhance the value of the current arrangement. The lifestyle changes required to enable an adult child to provide care or an elderly individual's attachment to a formal home health aide may lead to inertia in care arrangements. Similarly, moving to a nursing home requires substantial lifestyle changes as well as disinvestments that may be difficult to reverse such as selling a home. To capture the possibility of inertia, our models allow for positive true state dependence.

Alternatively, care arrangements may evolve over time as conditions change or as a caregiver experiences burnout. For example, an elderly individual's care arrangements may evolve as her health or that of her spouse deteriorates, her spouse dies, or formal care becomes more expensive. Accordingly, our models control for relevant time-varying characteristics that may affect families' caregiving decisions. Our models also allow the set of potential care arrangements to vary over time in response to changes in family structure. In addition, adult children may rotate the role of primary caregiver as a way to share the burden or as the caregiver experiences burnout. To capture the possibility of caregiver burnout, our models allow for negative true state dependence.

We develop and estimate three dynamic models of care. Two of these are discrete choice models, while the third is a continuous choice model. In the Multiple Caregiver Model, the family decides whether to use each potential care arrangement (institutional care, formal home health care, care provided by the spouse, and care provided by each particular child). This model allows for the possibility that the elderly individual relies on more than one caregiver or caregiving arrangement. In the Primary Caregiver Model, the family selects the primary care arrangement from all available alternatives. Finally, in the Hours of Care Model, the family determines hours in each potential care arrangement. Like the Multiple Caregiver Model, this model allows for multiple care arrangements.

In all of our models, we assume that each family has an underlying latent value for each potential care arrangement. More formally, consider family n that consists of one or two elderly individuals, J_n adult children, and up to J_n children-in-law. Elderly individual i may require care at time t. If she is married, her spouse may provide some or all of her care. In addition, each adult child or adult child-in-law is a potential caregiver. Depending on the model, the family decides whether to rely on each potential care arrangement, selects the primary care arrangement, or determines how much of each arrangement to use. Define the $J_n + 4$ caregiving alternatives as: no care, care provided by a spouse, formal home health care, care in a nursing home, and informal care from each of the J_n children or their spouses.

The latent value of care alternative j to individual i in family n at time t is denoted by:

$$y^*_{nijt} = X_{nit}\beta_j + Z_{njt}\gamma + \alpha_j y_{nijt-1} + \omega_{nijt}. \tag{1}$$

The vector X_{nit} includes exogenous characteristics of the elderly individual.[7] In particular, X_{nit} includes demographic characteristics and activity limitations that may influence an elderly individual's caregiving needs, opportunities, and preferences. The vector Z_{njt} includes exogenous characteristics of the potential care arrangements, namely demographics of the adult children and children-in-law and market conditions/public policies in the elderly individual's or household's state of residence.

The observed variable corresponding to the latent variable is given by y_{nijt}. As discussed in the following subsections, the exact definition of the corresponding observed variable varies with the model specification. The inclusion of y_{nijt-1} allows past choices to influence the current value of alternative j and, thus, captures the true dynamic component of long-term care decision-making. To distinguish between true state dependence (as captured by the α_j) and persistence in care arrangements due to unobserved heterogeneity (i.e., spurious state dependence), we allow for unobserved correlation across time (as captured by ω_{nijt}). We refer to α_j as true state dependence, which is alternative-specific in two of our models.

We decompose the random components of families' long-term care decisions, ω_{nijt}, into (at least) two types of unobserved heterogeneity as well as an idiosyncratic error term, ε_{nijt} :

$$\omega_{nijt} = u_{ni} + \eta_{nij} + \varepsilon_{nijt}.$$

[7] We augment the continuous choice model to allow for substitution across types of care.

Some elderly individuals may have preferences for certain care options that are not observed to the econometrician and hence not captured by X or Z. For example, a family may avoid institutional care due to a particularly strong philosophical or cultural reason. Such individual/family-alternative-specific correlation across time is captured by η_{nij}. In addition, there may be individual- or family-specific characteristics that influence all care alternatives across time but are unobserved to the econometrician. For example, high levels of wealth may enable a family to purchase formal care rather than to rely exclusively or primarily on family members. Such individual/family-specific correlation across time and alternatives is captured by u_{ni}. As shown in the following subsections, the assumed distributions of u_{ni}, η_{nij}, and ε_{nijt} vary across our three models to allow for experimentation with different error structures. For ease of exposition, we drop the family subscript in the following subsections.

3.1 Multiple Caregiver Model

In our Multiple Caregiver Model, the family decides whether to use each potential care arrangement by taking into account characteristics of the elderly individual, characteristics of the care arrangement, and whether the individual relied on that arrangement in the previous period. Excluding the dynamic component, this approach is similar to that of CS, Brown (2006), and BGHS. In this model, we assume that the family selects each arrangement with a positive latent value without considering interactions across care alternatives.

More technically, we estimate a dynamic multivariate probit model, where the baseline latent value of alternative j is given in equation (1). We assume $\varepsilon_{ijt} \sim iidN(0,1)$, $u_i \sim iidN(0,\sigma_u^2)$, and $\eta_{ij} \sim iidN\left(0,\sigma_\eta^2\right)$ and define $F_{u,\eta}(\cdot)$ as the joint distribution of u and η. Family n uses alternative j to provide care for individual i at time t if and only if

$$y_{ijt} = 1\left(y^*_{ijt} > 0\right).$$

Let

$$V^m_{ijt}(\theta^m) = X_{it}\beta_j + Z_{ijt}\gamma + \alpha_j y_{ijt-1} + u_i + \eta_{ij},$$

where y_{ijt-1} equals one if alternative j was chosen last period, $\theta^m = (\beta,\gamma,\alpha,\sigma_\eta,\sigma_u)$ is the vector of parameters to estimate, and the m superscript denotes Multiple Caregiver Model.

Then, the likelihood contribution for an elderly individual i is

$$\mathcal{L}_i = \int \int \prod_t \prod_j \Phi\left(V_{ijt}^m\right)^{y_{ijt}} \left[1 - \Phi(V_{ijt}^m)\right]^{1-y_{ijt}} dF_{u,\eta}(u, \eta).$$

3.2 Multiple Caregiver Results

Table 4 presents the multivariate probit results. Several demographic characteristics significantly influence the value of each potential care arrangement.[8] For example, controlling for marital status, age, activity limitations, educational attainment, and several characteristics of the spouse, white families value each mode of care more highly for men than for women. Most of these gender gaps are more pronounced among black and Hispanic elderly individuals. Although inconsistent with some of the findings in the literature (e.g., McGarry, 1998; Pezzin and Schone, 1999b; CS), the implication that families value informal care more highly for elderly men than for elderly women is consistent with the implications of the game-theoretic analysis in BGHS; specifically, BGHS suggest that care provided to mothers is less effective (albeit also less burdensome) than care provided to fathers.

Activity limitations and age significantly influence the value of care arrangements. The value of each mode of care depends positively on the number of ADL and IADL problems experienced by an elderly individual. Controlling for activity limitations, informal care is less valuable as the individual ages.

Consistent with the literature (e.g., Stern 1995), our results imply that spouses are an important source of care for one another. At first glance, the large, negative parameter estimates associated with marital status for the other care arrangements appear to suggest that families value non-spousal care arrangements significantly more highly for unmarried than for married elders. However, parameter estimates associated with the spouse's characteristics mitigate or dominate the direct effect of marital status, so that the average marginal effect of having a spouse on the other care choices is positive. For example, as the spouse

[8] In this section, our discussion focuses on the relationship between each characteristic and the latent value of using a particular mode of care relative to the outcome where the individual does not use that mode of care. In a separate section, we present and discuss the marginal effects associated with the most policy-relevant variables. For a complete set of marginal effects, please see www.people.virginia.edu/~sns5r/resint/ltcstf/dynamicmarginaleffects.html

ages, all forms of care increase in value. The spouse's IADL problems reduce the value of spousal care while enhancing the value of care provided by a child or a home health aide.[9]

	Informal Care by Spouse		Informal Care by Child		Formal Home Health Care		Institutional Care	
Variable	Estimate	Std Err	Estimate	Std Err	Estimate	Std Err	Estimate	Std Err
True State Dependence Effect	0.795 **	0.078	1.426 **	0.097	1.070 **	0.188	2.158 **	0.424
Parent and Spouse Characteristics								
Constant	-3.815 **	0.182	-1.565 **	0.282	-2.066 **	0.910	-6.307 **	2.051
Female	-0.308 **	0.079	-0.758 **	0.068	-0.566 **	0.144	-0.762 **	0.170
Black	0.176	0.213	0.123	0.299	-0.168	0.371	0.335	0.383
Hispanic	0.510	0.346	-0.164	0.551	0.069	0.332	-0.381	0.712
Female*Black	-0.619 **	0.277	-0.619 **	0.314	0.112	0.541	-0.762	0.529
Female*Hispanic	-1.529 **	0.543	-0.296	0.687			-4.117	1372.4
Married			-4.436 **	0.258	-2.548 **	0.898	-5.630 **	0.958
Age	-0.013 **	0.006	-0.015 **	0.003	-0.003	0.006	-0.001	0.006
Spouse Age	0.044 **	0.006	0.051 **	0.003	0.036 **	0.008	0.075 **	0.009
HS Diploma	-0.059	0.101	0.152 **	0.076	0.210	0.166	0.078	0.221
College Degree	-0.090	0.107	0.027	0.088	0.139	0.179	0.205	0.205
Spouse HS Diploma	0.141	0.101	-0.194 *	0.103	0.082	0.216	0.210	0.317
Spouse College Degree	-0.123	0.107	-0.216 *	0.134	0.095	0.236	-0.288	0.335
# ADLs	0.059 **	0.025	0.057 **	0.016	0.144 **	0.034	0.199 **	0.051
# IADLs	0.442 **	0.028	0.295 **	0.021	0.208 **	0.048	0.255 **	0.053
# Spouse ADLs	0.033	0.029	0.035	0.037	0.092 *	0.056	0.110	0.085
# Spouse IADLS	-0.100 **	0.029	0.170 **	0.046	0.132 **	0.058	0.137	0.096
Child Characteristics								
Female			0.293 **	0.065				
Female*Black			-0.234	0.339				
Female*Hispanic			-0.035	0.499				
Age			-0.001	0.005				
Education			0.020	0.016				
# Kids			-0.014	0.023				
Working			-0.002	0.002				
Married			-0.069	0.079				
Child Lives Within 10 Miles			0.395 **	0.067				
Child Lives With Parent			0.910 **	0.102				
Local Characteristics								
Home Health Care Per Week ($100)					-2.075 **	0.655		
Medically Needy Program					0.174	0.398	0.081	0.353
SSI Income Limit 1 Person ($1000)					1.764 *	1.131	1.263	1.033
SSI Income Limit 2 Person ($1000)					0.801 *	0.505	-0.462	0.679
Ln(NH Beds Per Population > 70)							0.018	0.189
ADL Score							-0.173	0.342
Nursing Hours							1.044 **	0.299
Standard Deviation Person-Alternative Error (Restricted)					0.001			
Standard Deviation Person Error					0.618 **	0.037		

Table 4: Multiple Caregiver: Multivariate Probit Estimates

Our results also shed light on the role of adult children's characteristics in families' long-term care arrangements for elderly individuals. Consistent with the literature (e.g., SPH; Wolf, Freedman and Soldo, 1997; CS; ES), child gender is associated with informal care

[9] One cannot include a variable for marital status in the spousal care value because a spouse can provide care only if she exists; thus the MLE of such a parameter would be infinity.

provision. In white families, daughters are valued more highly than sons as caregivers, after controlling for other demographic characteristics. The effects of child gender in Black and Hispanic families are smaller and not statistically significant. Children who live with or near their elderly parents are valued more highly as caregivers.[10]

Several market conditions and public policies in the elderly individual's state of residence also significantly influence care arrangements. After controlling for activity limitations, the attractiveness of formal home health care depends negatively on the average wages of home health care providers and positively on the generosity of a state's income limits for Medicaid coverage of formal modes of care. Institutional care is a more attractive option in states with greater nursing home staff hours per nursing home resident.

The results of this model highlight the importance of controlling for unobserved heterogeneity over time, as the estimate of the standard deviation of the person error (σ_η) is large and significant. Unobserved characteristics such as wealth and chronic health conditions unrelated to ADL and IADL problems may contribute to spurious state dependence in care arrangements. Moreover, the results indicate that there is significant positive true state dependence – or inertia – across all caregiving choices. This finding probably reflects the substantial economic and psychological costs associated with transitions from one care arrangement to another. To the extent that caregiver burnout contributes to negative true state dependence, its effect is dominated by inertia.

We also estimated a static multivariate probit model where care arrangements in the previous period do not influence current care arrangements (i.e., we restrict $\alpha_j = 0$). Most of the parameter estimates associated with the static model are consistent in sign with those of the dynamic model, but their magnitudes tend to be larger and more statistically significant. For example, the relationship between the generosity of a state's Medicaid policy and the value of formal home health care is larger and more statistically significant in the static model. Perhaps some characteristics matter more in the initial choice of the care arrangement than in the current decision conditional on past decisions. Also, in the model

[10] Later in the paper, we address the potential endogeneity of geographic distance. In particular, we test whether the role of the child's initial (exogenous) location relative to the parent differs from the role of the child's current (potentially endogenous) location relative to the parent.

with dynamics, the measured effects may be associated with flows, while, in the static model, the measured effects may be associated with a stock of present and future flows (e.g., Berkovec and Stern, 1991).

Evidence of inertia in care arrangements and the sensitivity of parameter estimates across our static and dynamic models underscore the importance of developing models that capture intertemporal patterns of care. As discussed earlier, most of the models in this literature are static (e.g., SPH; PSa; ES; PPS; BGHS). While a few studies present dynamic models (GM; BKM; DL; HM; Gardner and Gilleskie, 2009), our models encompass a broader range of care arrangements.

3.3 Primary Caregiver Model

Much of the long-term care literature focuses on the selection of the primary care arrangement for an elderly individual (e.g., HS; ES), but all of the existing models of the primary care arrangement are static in nature. In our Primary Caregiver Model, the family selects the primary care arrangement for an elderly individual in a particular time period taking into account the characteristics of the potential care recipient, the characteristics of the potential care arrangements, and the primary care arrangement selected the previous period. The primary care arrangement is the arrangement with the highest latent value. If the value of each potential care arrangement is less than the value of remaining independent, the individual receives no care.

More technically, we estimate a multinomial mixed logit model (McFadden and Train, 2000) where the baseline latent value to alternative j is given in equation (1) with one modification. In particular, in Table 4, we see that the estimate of the standard deviation of the individual/alternative-specific unobserved heterogeneity effect is very small. Since our priors are that there is some important source of individual/alternative-specific unobserved heterogeneity, we try modelling it in a different way. We augment the baseline latent value given in equation (1) to incorporate individual/time-specific unobserved heterogeneity, denoted v_{it}. Specifically, unobserved components are now given by

$$\omega_{ijt} = \delta_j u_i + \lambda_j v_{it} + \eta_{ij} + \varepsilon_{ijt}, \tag{2}$$

where we assume $u \sim iidN(0, \Omega_u)$, $v_t \sim iidN(0, \Omega_v)$, $\eta_j \sim iidN(0, \Omega_\eta)$, and $\varepsilon_{ijt} \sim iidEV$. The δ_j and λ_j terms are alternative-specific factor loadings. The variance terms of Ω_u and Ω_v are restricted to one for identification, and the off-diagonal terms are estimated. The off-diagonal terms are transformed to $\frac{2e^{\vartheta_u}}{1+e^{\vartheta_u}} - 1$ to insure that $-1 \leq \Omega_{u21} \leq 1$, which is necessary for positive-definiteness.[11] The variance and correlation terms of Ω_η are estimated using transformations, $\Omega_{\eta ii} = \exp\{\nu_{\eta i}\}$ for the variance terms (to insure positive terms) and the correlation in the same way as for Ω_{u21}.

Assume the family chooses the alternative that provides the highest latent value; i.e.,

$$y_{ijt} = 1\left(y^*_{ijt} \geq y^*_{ikt} \forall k \neq j, k \in S_{it}\right),$$

where the set of care alternatives at time t is denoted S_{it}. Let

$$V^p_{ijt}(\theta^p) = X_{it}\beta_j + Z_{ijt}\gamma + \alpha y_{ijt-1} + \delta_j u_i + \lambda_j v_{it} + \eta_{ij}, \tag{3}$$

with parameters given by $\theta^p = (\beta, \gamma, \alpha, \delta, \lambda, \Omega_u, \Omega_v, \Omega_\eta)$ (the p superscript denotes Primary Caregiver Model). The lagged care decision, y_{ijt-1}, is a dummy variable equal to one if care arrangement j was the primary arrangement in the previous period. Let a_{it} be a dummy variable indicating whether individual i is living at time t. Then the likelihood contribution for family n is

$$\mathcal{L}_n = \int\int\int \prod_i \prod_t \left(\frac{\exp\{V^p_{ijt}\}}{\sum_{k\in S_{it}} \exp\{V^p_{ikt}\}} \right)^{a_{it}} dF_{u,\eta,v}(u, \eta, v) \tag{4}$$

where $F_{u,\eta,v}(\cdot)$ is the joint distribution of the unobservables. There is no closed form solution to equation (4), so we estimate the model using maximum simulated likelihood estimation. The simulated likelihood contribution is

$$\mathcal{L}_n = \frac{1}{R}\sum_{r=1}^{R} \prod_i \prod_t \left(\frac{\exp\{V^p_{ijt}(\eta^r_{ij}, u^r_i, v^r_{it}, \theta^p)\}}{\sum_{k\in S_{it}} \exp\{V^p_{irt}(\eta^r_{ik}, u^r_i, v^r_{it}, \theta^p)\}} \right)^{a_{it}},$$

where $(\eta^r_{ij}, u^r_i, v^r_{it})$ are errors simulated from their respective densities (BKM; Hajivassiliou, McFadden, and Ruud, 1996).[12]

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[11] The variance terms of Ω_u are restricted to be one because u_i is multiplied by an alternative-specific factor loading (δ_j), so the variance terms are not identified.

[12] We use antithetic acceleration in simulation. Geweke (1988) shows that if antithetic acceleration is

3.4 Primary Caregiver Results

Table 5 presents multinomial mixed logit parameter estimates for the choice of the primary care arrangement. Consistent with the Multiple Caregiver Model, the results of the Primary Caregiver Model provide evidence that inertia plays a role in elder care arrangements. That is, we find statistically significant, positive state dependence in the choice of the primary care arrangement after controlling for observed and unobserved heterogeneity. While caregiver burnout could motivate family members – particularly siblings – to alternate the role of primary caregiver, the sign and statistical significance of the relevant parameter estimate suggests that the impact of burnout is dominated by inertia.

The roles of demographic characteristics and activity limitations in the decision to use a particular mode of care are generally similar to their roles in the selection of the primary care arrangement.[13] For example, as an elderly individual develops more activity limitations, the value of each potential mode of care significantly increases as an *arrangement* (in Table 4) and as the *primary care arrangement* (in Table 5). Similarly, marriage, by itself, significantly reduces the value of non-spousal care arrangements, both overall and as the primary arrangement. However, as in the Multiple Caregiver Model, as the elderly individual's spouse ages, the attractiveness of alternative care arrangements increases significantly, neutralizing the direct effect of marriage, while the attractiveness of spousal care as an arrangement and as the primary arrangement falls significantly.

Although the Primary Caregiver Model explicitly controls only for health limitations that relate to ADLs and IADLs, the person-time-choice factor loadings (λ_j) may capture the role of temporary health conditions unrelated to ADL or IADL limitations. Estimates for these factor loadings indicate that person-time-specific heterogeneity significantly influences the values of the two informal care arrangements. Thus, the results of this model suggest that temporary health conditions unrelated to ADL and IADL limitations may change the relative attractiveness of each informal care mode and hence may induce a change in the

implemented during simulation, then the loss in precision is of order $1/N$ (where N is the number of observations), which requires no adjustment to the asymptotic covariance matrix.

[13] Again our discussion focuses on the relationship between each characteristic and the latent value of using a particular mode of care relative to the outcome where the individual does not use that mode of care. Later we present and discuss selected marginal effects.

individual's primary care arrangement.

Variable	Estimate	Std Err	Informal Care by Spouse Estimate	Std Err	Informal Care by Child Estimate	Std Err	Formal Home Health Care Estimate	Std Err	Institutional Care Estimate	Std Err
True State Dependence Effect	1.129 **	0.066								
Parent and Spouse Characteristics										
Constant			-2.330 **	0.366	-4.325 **	0.930	-5.279 **	2.622	-15.769 **	5.019
Female			-1.291 **	0.183	-3.355 **	0.283	-2.726 **	0.394	-4.108 **	0.566
Black			-0.321	0.274	-1.391 **	0.361	-0.357	0.695	-0.274	0.666
Hispanic			0.142	0.521	-0.125	0.422	-0.458	1.062		
Married					-6.899 **	1.344	-8.150 **	3.420	-8.632 **	3.112
Age			0.048 **	0.016	-0.012	0.010	0.026	0.017	0.030	0.020
Spouse Age			-0.036 **	0.016	0.075 **	0.016	0.110 **	0.032	0.127 **	0.033
HS Diploma			-0.042	0.187	0.318	0.241	0.761 *	0.449	0.384	0.525
College Degree			-0.253	0.199	0.129	0.259	0.609	0.462	0.563	0.477
Spouse HS Diploma			0.085	0.190	-0.888 **	0.367	0.140	0.819	0.162	0.772
Spouse College Degree			-0.155	0.202	-0.645 *	0.406	-0.029	0.770	-0.888	0.882
# ADLs			0.084 *	0.046	0.097 *	0.055	0.201 **	0.081	0.477 **	0.119
# IADLs			0.763 **	0.057	0.802 **	0.068	0.674 **	0.117	0.912 **	0.131
# Spouse ADLs			0.133 **	0.062	0.127	0.110	0.315 *	0.170	0.206	0.199
# Spouse IADLS			-0.128 **	0.065	0.515 **	0.131	0.215	0.187	0.475 **	0.219
Person-Time-Choice Factor Loading			-0.426 **	0.107	0.199 *	0.125	0.056	0.299	-0.081	0.272
Person-Choice Factor Loading			0.256 **	0.106	1.026 **	0.141	0.770 **	0.244	1.514 **	0.261
Child Characteristics										
Female					0.659 **	0.134				
Age					0.009	0.012				
Education					0.067 *	0.040				
# Kids					-0.036	0.048				
Working					-0.004	0.004				
Married					-0.701 **	0.190				
Child Lives Within 10 Miles					0.816 **	0.177				
Child Lives With Parent					2.257 **	0.236				
Local Characteristics										
Home Health Care Per Week ($100)							-4.478 **	1.788		
Medically Needy Program							0.430	1.030	0.123	0.807
SSI Income Limit 1 Person ($1000)							4.535 *	2.552	3.749 *	2.323
SSI Income Limit 2 Person ($1000)							1.131	1.625	-0.636	1.530
Ln(NH Beds Per Population > 70)									-0.118	0.376
ADL Score									-0.665	0.771
Nursing Hours									2.549 **	0.668
Person-Time Effect Father-Mother	-1.000									
Person Effect Father-Mother	-1.000									
Cholesky Term Father	0.327 **	0.106								
Cholesky Term Mother	0.146	0.121								
Cholesky Term Father-Mother	-0.821 **	0.098								

Notes: The parameter estimate in the Cholesky decomposition for the Person-Time Effect was diverging to negative infinity so we restricted it to exp(-7), which implies a Person-Time Effect of -1.000. The same applies in the case of the Person Effect.

Table 5: Primary Caregiver: Multinomial Mixed Logit Estimates

In the absence of information concerning income and wealth, education may serve as a proxy for financial well-being. As in the Multiple Caregiver Model, the results suggest a limited influence of education on the value of potential care arrangements. However, the person-choice factor loading (δ_j) estimates indicate that person-specific unobservables – such as wealth – which influence all care alternatives across time, are significantly related to the value of each potential mode of care as the primary care arrangement.

The implications concerning the characteristics of the younger generation are similar across the discrete choice models. Again families value daughters more than sons as caregivers, and proximity to or co-residence with elderly parents enhances the value of care provided by an adult child. Although a child's marital status is not significantly related to her value as a caregiver, marriage significantly reduces her value as the primary caregiver.

Again several market conditions and public policies significantly influence the value of formal care arrangements in both discrete choice models. For example, the value of formal home health care as an arrangement or as the primary arrangement depends negatively on the cost of home health aide workers. Similarly, the value of institutional care depends positively on the nursing home staff hours per resident in the individual's state of residence.

3.5 Hours of Care Model

An important dimension of caregiving decisions concerns how much care to provide. Following SPH, Wolf, Freedman, and Soldo (1997), Pezzin and Schone (1999b), CS, and BGHS, we next consider the continuous choice associated with caregiving alternatives. As discussed earlier, families may rely on more than one mode of care. For example, an elderly individual may receive informal care provided by a child together with formal care provided by a home health aide. As this example suggests, various caregiving alternatives – and the amount provided – may be substitutable to some extent. Moreover, the quantity of care received in the past could impact the value associated with the quantity of that care alternative provided today. Accordingly, our Hours of Care Model allows for the possibility of multiple care arrangements, while linking arrangements over time.

We estimate a dynamic multivariate tobit model, where we augment the baseline latent value of care in equation (1) to allow for substitution across modes of care as well as different effects of true state dependence. Specifically, the latent value associated with the amount of time spent using the jth care arrangement is given by

$$y^*_{ijt} = X_{it}\beta_j + Z_{ijt}\gamma + \rho_j \sum_{j' \neq j} y_{ij'} + \alpha_j^{\text{thresh}} 1\left(y_{ijt-1} > 0\right) + \alpha_j^{\text{marg}} y_{ijt-1} + \omega_{ijt}, \tag{5}$$

where the observed continuous value of caregiving is given by $y_{ijt} = \max(0, y^*_{ijt})$. As in CS, substitution in total care provided across alternatives is captured by $\rho_j \sum_{j' \neq j} y_{ij'}$. The α_j terms capture true state dependence in caregiving where the amount of care provided of mode j depends both on whether j was chosen in the previous period (captured by the threshold value of true state dependence, α^{thresh}) as well as the quantity of alternative j provided in the previous period (captured by the marginal value of true state dependence, α^{marg}).[14]

Similar to the Primary Caregiver Model, this model decomposes the random components of families' long-term care decisions into three types of unobserved heterogeneity as well as an idiosyncratic error term:

$$\omega_{ijt} = u_i + \eta_{ij} + v_{it} + \varepsilon_{ijt},$$

where $u_i \sim iidN\left(0, \sigma_u^2\right)$, $\eta_{ij} \sim iidN\left(0, \sigma_\eta^2\right)$, $v_{it} \sim iidN\left(0, \sigma_v^2\right)$, and $\varepsilon_{ijt} \sim iidN\left(0, \sigma_\varepsilon^2\right)$. The parameters to estimate are σ_ε and $\theta^h = (\alpha, \beta, \gamma, \rho, \sigma_u, \sigma_\eta, \sigma_v)$ (the h superscript denotes Hours of Care Model). Let

$$V_{ijt}^h\left(\theta^h\right) = X_{it}\beta_j + Z_{ijt}\gamma + \rho_j \sum_{j' \neq j} y_{ij'} + \alpha_j^{\text{thresh}} 1\left(y_{ijt-1} > 0\right) + \alpha_j^{\text{marg}} y_{ijt-1} + u_i + \eta_{ij} + v_{it}.$$

The set of values A_n of the idiosyncratic error ε that results in the amount of time spent using the jth care provision is given by

$$A_n \equiv \left\{ \varepsilon : \varepsilon_{ijt} \begin{cases} = y_{ijt} - V_{ijt}^h(\theta^h) & \text{if } y_{ijt} > 0 \\ \leq -V_{ijt}^h\left(\theta^h\right) & \text{if } y_{ijt} = 0 \end{cases} \right\}.$$

[14] Equation (5) is a set of structural equations, one for each alternative available to the family. If we ignore the nonnegativity constraints on y_{ij}, we can solve equation (5) to get a reduced form set of equations. CS show how to add the nonnegativity constraints in an algorithm that handles nonlinearity of the reduced form. They state that the nonnegativity constraints lead to the potential for multiple equilibria. The most common cause of multiple equilibria is the inclusion of a discrete dependent variable. For example, if we were to include a term such as $\sum_{j' \neq j} 1\left(y_{ij't} > 0\right)$ or $1\left(\sum_{j' \neq j} y_{ij't} > 0\right)$ on the right-hand side of equation (5), then we would have a generalization of the problem discussed in the entry literature (Bresnahan and Reiss, 1991; Tamer, 2003; and Goeree and Stern, 2010). Fontaine, Gramain, and Wittwer (2009) estimate a model of family long-term care decisions with only binary interactions using an estimation technology from Tamer (2003). In this work, we focus on the structural equations directly; we do not address issues of multiple equilibria but treat the observed outcome as the only equilibrium.

The likelihood contribution for an individual i is

$$\mathcal{L}_i = \int_{A_n} \prod_t \prod_j \left\{ \frac{1}{\sigma_\varepsilon} \phi \left(\frac{y_{ijt} - V_{ijt}^h \left(\theta^h\right)}{\sigma_\varepsilon} \right) \right\}^{1(y_{ijt}>0)} \left\{ 1 - \Phi \left(\frac{V_{ijt}^h \left(\theta^h\right)}{\sigma_\varepsilon} \right) \right\}^{1(y_{ijt}=0)} dF_{u,\eta,v}(u, \eta, v). \tag{6}$$

where $F_{u,\eta,v}(\cdot)$ denotes the joint distribution of the unobservables. We simulate equation (6) using GHK. Estimating the asymptotic covariance matrix is standard (Geweke, 1991).

3.6 Hours of Care Results

Table 6 presents the results of our dynamic multivariate tobit model. The results of this Hours of Care Model reinforce the importance of controlling for unobserved heterogeneity over time, as the estimate of the standard deviation of the person error (σ_η) is relatively large and statistically significant. All modes of care exhibit statistically significant true state dependence. The quantity of each mode of informal care in the current period depends positively on the use of that mode of care in the previous period – a threshold inertia effect – and on the quantity provided in the previous period – a marginal inertia effect. The quantity of formal home health care in the current period exhibits threshold inertia, while the quantity of institutional care exhibits marginal inertia. Thus, the results again indicate that, to the extent that caregiver burden influences long-term care arrangements, its impact is dominated by inertia.

Contrary to our expectations and to the literature (e.g., CS and Van Houtven and Norton, 2004), the estimated substitution effects indicate that the quantity of each mode of care depends positively on the total amount of care currently received from other sources. The positive effects associated with informal care provided by a child may capture competition among children for a bequest (Bernheim, Shleifer, and Summers, 1985). However, a bequest motive of this sort would not explain positive effects associated with the other modes of care. Instead these might reflect parent-specific unobserved heterogeneity not captured by our model specification.

Most characteristics that significantly increase (decrease) the latent value of using a particular mode of care also significantly increase (decrease) hours spent in that mode. For example, ADL and IADL problems increase the attractiveness of formal as well as informal care arrangements. Likewise, hours in each arrangement depend positively on the number of ADL and IADL problems. Consistent with expectations as well as the implications of the discrete-choice models, adult children who live with or near their elderly parents provide more assistance than do their geographically distant counterparts.

Variable	Informal Care by Spouse Estimate	Informal Care by Spouse Std Err	Informal Care by Child Estimate	Informal Care by Child Std Err	Formal Home Health Care Estimate	Formal Home Health Care Std Err	Institutional Care Estimate	Institutional Care Std Err
Substitution Effect	0.167 **	0.053	0.348 **	0.048	0.289 **	0.060	0.759 **	0.062
True State Dependence Effects								
Threshhold Effect	0.176 **	0.051	0.364 **	0.045	0.402 **	0.084	0.334	0.243
Marginal Effect	0.214 *	0.110	0.521 **	0.198	0.126	0.140	1.173 **	0.345
Parent and Spouse Characteristics								
Constant	-1.253 **	0.042	-0.645 **	0.091	-1.013 **	0.274	-2.726 **	0.667
Female	-0.134 **	0.024	-0.273 **	0.028	-0.225 **	0.054	-0.297 **	0.053
Black	-0.013	0.055	-0.109 **	0.045	-0.032	0.091	0.028	0.086
Hispanic	0.044	0.097	-0.078	0.078	0.050	0.107		
Married			-1.428 **	0.045	-0.731 **	0.225	-1.441 **	0.157
Age	-0.006 **	0.002	-0.004 **	0.000	0.001	0.001	0.001	0.001
Spouse Age	0.016 **	0.002	0.016 **	0.000	0.011 **	0.001	0.022 **	0.001
HS Diploma	-0.025	0.033	0.053 *	0.032	0.104 *	0.065	0.016	0.089
College Degree	-0.051	0.036	0.005	0.035	0.086	0.068	0.095	0.075
Spouse HS Diploma	0.037	0.033	-0.075 *	0.042	0.028	0.091	0.059	0.099
Spouse College Degree	-0.050	0.037	-0.102 **	0.051	0.037	0.094	-0.189 *	0.111
# ADLs	0.032 **	0.008	0.013 *	0.007	0.048 **	0.013	0.081 **	0.016
# IADLs	0.139 **	0.011	0.098 **	0.009	0.088 **	0.018	0.095 **	0.016
# Spouse ADLs	0.007	0.010	0.002	0.015	0.033	0.022	0.025	0.024
# Spouse IADLS	-0.029 **	0.011	0.059 **	0.019	0.038 *	0.023	0.079 **	0.027
Child Characteristics								
Female			0.086 **	0.027				
Age			-0.001	0.001				
Education			0.005	0.006				
# Kids			-0.005	0.009				
Working			-0.001	0.001				
Married			-0.022	0.033				
Child Lives Within 10 Miles			0.126 **	0.030				
Child Lives With Parent			0.313 **	0.040				
Local Characteristics								
Home Health Care Per Week ($100)					-0.800 **	0.255		
Medically Needy Program					0.052	0.055	-0.096	0.114
SSI Income Limit 1 Person ($1000)					-0.057	0.113	0.599 *	0.360
SSI Income Limit 2 Person ($1000)					0.459 **	0.103	-0.246	0.194
Ln(NH Beds Per Population > 70)							0.055	0.129
ADL Score							0.773 **	0.392
Nursing Hours							0.286	0.201
Std Dev for Parent Effect			0.181 **	0.014				
Std Dev for Parent-Alternative Effect (Restricted)			0.001					
Std Dev for Parent-Time Effect			0.040 **	0.018				
Std Dev for Idiosyncratic Effect			0.402 **	0.008				

Notes: The standard deviation for the Parent-Alternative effect was close to zero so we restricted it to exp(-7).

Table 6: Hours of Caregiving: Multivariate Tobit Estimates

Market conditions and public policies significantly influence the quantity of formal care received by the elderly individual. Consistent with our other models, the quantity of formal home health care depends negatively on the average wages of home health care providers. The quantity of institutional care depends positively on the generosity of a state's Medicaid limits facing individuals, while the quantity of formal home health care depends positively on the generosity of a state's Medicaid limits facing couples.

4 Policy Implications

For each of our dynamic models, we present the marginal effects associated with the characteristics that have the most relevance from a public policy perspective. In particular, Table 7 displays the marginal effects associated with the market conditions and public policies in the elderly individual's state of residence.

The cost of formal home health care influences the family's long-term care decisions. As indicated in the top panel of Table 7, as the weekly cost of full-time formal home health care increases by \$100, the predicted probability that the elderly individual receives this mode of care falls by 5 percentage points. As shown in the middle panel, the cost of formal home health care also influences the selection of the primary care arrangement. In response to a \$100 increase in the weekly cost of full-time care, the predicted probability of relying on formal home health care as the primary arrangement falls by 3.3 percentage points, while the predicted probability of living independently increases by 2.1 percentage points.[15] Finally, as shown in the bottom panel, conditional on receiving formal home health care, an increase of \$100 in its weekly cost is associated with a 6.2 percentage point reduction (about 10.4 hours) in the predicted quantity of formal home health care.

The existing literature provides mixed evidence concerning the effects of state-level Medicaid policy on nursing home utilization. Cutler and Sheiner (1994) report a positive and statistically significant relationship between the presence of a medically needy program and the probability of nursing home use. Similarly, ES suggest that the presence of a medically

[15] The marginal effects associated with the Primary Caregiver Model sum to one. As a result of rounding error the marginal effects associated with independent living may differ from one minus the sum of the marginal effects reported in the Table 7.

needy program enhances the value of nursing home care. In contrast, Aykan (2002) does not find a statistically significant relationship between the presence of a medically needy program and the likelihood of institutional care. Likewise, Grabowski and Gruber (2007) report that the availability of a spend-down program is not statistically significantly associated with nursing home use. Consistent with Aykan (2002) and Grabowski and Gruber (2007), the presence of a medically needy program is not statistically significantly associated with the use of institutional care in our models. However, our Multiple Caregiver Model indicates that the presence of a medically needy program is associated with a 0.4 percentage point increase in the predicted probability of using formal home health care.

	Informal Care by Spouse			Informal Care by Child			Formal Home Health Care			Institutional Care		
Variable	Effect		Std Err	Effect		Std Err	Effect		Std Err	Effect		Std Err
Multiple Caregiver Model												
Average Probability	0.162	**	0.00	0.173	**	0.002	0.045	**	0.00	0.037	**	0.00
Home Health Care Per Week ($100)							-0.050	**	0.002			
Medically Needy Program							0.004	**	0.001	0.001		0.001
SSI Income Limit 1 Person ($1000)							0.043	**	0.004	0.021	**	0.003
SSI Income Limit 2 Person ($1000)							0.019	**	0.002	-0.007	**	0.002
Ln(NH Beds Per Population > 70)										0.000		0.000
ADL Score										-0.003	**	0.001
Nursing Hours										0.016	**	0.001
Primary Caregiver Model												
Average Probability	0.078	**	0.008	0.036	**	0.011	0.009	**	0.002	0.010	**	0.002
Home Health Care Per Week ($100)	0.008	**	0.004	0.003	**	0.001	-0.033	**	0.015	0.003	*	0.002
Medically Needy Program	-0.001		0.002	0.000		0.001	0.003		0.007	0.001		0.005
SSI Income Limit 1 Person ($1000)				-0.004	**	0.016	0.020		0.013	0.014		0.010
SSI Income Limit 2 Person ($1000)	-0.001		0.004	0.000		0.001	0.003		0.005	-0.002		0.003
Ln(NH Beds Per Population > 70)	0.000		0.000	0.000		0.000	0.000		0.000	-0.001		0.001
ADL Score	0.001		0.001	0.001		0.001	0.000		0.000	-0.004		0.005
Nursing Hours	-0.005	**	0.002	0.000		0.001	0.003	**	0.001	0.017	**	0.005
Hours of Care Model												
Average Conditional Probability	0.2154	**	0.002	0.1335	**	0.001	0.1217	**	0.008	0.1078	**	0.015
Home Health Care Per Week ($100)							-0.062	**	0.007			
Medically Needy Program							0.004		0.004	-0.006		0.004
SSI Income Limit 1 Person ($1000)							0.034	**	0.010	0.021		0.017
SSI Income Limit 2 Person ($1000)							0.012	**	0.003	0.006		0.046
Ln(NH Beds Per Population > 70)										0.004	**	0.001
ADL Score										-0.003		0.003
Nursing Hours										0.030	**	0.012
Number of Observations	3928			18298			9330			9330		

Notes: The reported marginal effects are the average marginal effects across all years. ** indicates significance at the 5% level; * indicates significance at the 10% level. Hours of care marginal effects are conditional on providing any care and are measured in terms of the proportion of total time.

Table 7: Marginal Effects for Market Conditions and Public Policies

Care arrangements depend on the generosity of the state's income limits for Medicaid eligibility. In response to a $1000 increase in the annual income limit facing unmarried individuals, the predicted probabilities that a lone elder relies on formal home health care or institutional care respectively increase by 4.3 and 2.1 percentage points. The positive and statistically significant relationship between income limits and nursing home use is consistent with economic theory and Gardner and Gilleskie (2009) but inconsistent with Grabowski and Gruber (2007). It is worth noting that Grabowski and Gruber (2007) set income limits to zero in states with spend-down provisions, while we use the actual income limits for all states. Among lone elders who receive formal home health care, predicted hours increase by 5.7 hours per week as the income limit increases by $1000. In general, the effects of income limits are smaller but qualitatively similar for married individuals. However, for married elders, the likelihood of institutional care is negatively associated with the income limit.

The use of institutional care depends on the quality and availability of care in the elderly individual's state of residence. For example, in response to an additional staff hour per resident, the predicted probability of relying on institutional care as the primary care arrangement increases by 1.7 percentage points. Among nursing home residents, the predicted quantity of care increases by about 5 hours per week in response to an additional staff hour per resident and by about 40 minutes per week in response to a one percent increase in the number of nursing home beds per elderly resident.

5 Specification and Robustness Checks

In this section, we address several limitations of our data and models. First, given the poor quality of our income and wealth data, we explore the implications of excluding income and wealth from our models. Second, we test whether state/arrangement-specific effects and other state-specific effects not captured in our models influence care arrangements. Finally, we examine whether the distance between an elderly parent and an adult child is endogenous.

5.1 Income and Wealth Data

As we discussed in section 2, the measures of income and assets/wealth in the AHEAD/HRS may not be reliable. Therefore, our models do not control for income or wealth. Here we present several alternative specifications to test whether adding income or wealth would significantly improve the fit of our models. In light of the findings in Gardner and Gilleskie (2009) that an important effect of wealth operates through its interactions with state Medicaid rules, we also examine interactions of income and wealth with policy characteristics. To facilitate comparison with Gardner and Gilleskie (2009) and BGHS, we use 1989 and 1993 Medicaid income and asset limits as well as dummy variables indicating the presence of a medically needy program. For each model, we estimate several additional specifications. In addition to income or wealth, these specifications include income or wealth interacted with Medicaid income or asset limits as well as the presence of a medically needy program. One of the wealth specifications excludes observations with missing information on wealth. Since the lack of information concerning wealth may not be random, the remaining wealth specifications include a dummy variable for missing wealth data.[16] While Gardner and Gilleskie (2009) treat the Medicaid asset limit as a discrete cutoff, our approach accommodates the possibility that individuals just above the limit may spend down and thus behave similarly to those who are just below the limit.[17] In particular, we include "smoothed" assets in our third wealth specification.[18] To reduce the influence of large fluctuations in reported wealth, the final specification replaces the individual's current wealth with her average wealth over the observed time frame.

[16] Wealth includes all assets. We use SSI Medicaid income limits for singles or couples, depending on the individual's marital status. Although adding dummy variables is a common way to handle missing values, Abbrevaya and Donald (2011) suggest that this approach may not always provide the desired result.

[17] Norton (1995) reports evidence that welfare aversion among the elderly actually leads to the opposite pattern as individuals seek to avoid Medicaid eligibility.

[18] Let W_{it} be the wealth of family i at time t, and let C_i be the state-specific asset limit. The smoothed asset limit rule we apply is

$$W_{it}^{*} = \begin{cases} \log\left(W_{it} + 1 - C_i\right) & \text{if } W_{it} \geq C_i \\ \log\left(C_i + 1 - W_{it}\right) & \text{if } W_{it} < C_i \end{cases} .$$

Model	Specification	Joint Chi-Square Test Statistic	Joint Critical Value	Individual Chi-Square Test Statistics Income or Wealth Interacted with: Constant	Medically Needy Program	Medicaid Limit	Missing Wealth	Critical Value
Income and Income interactions:								
Multiple Caregiver								
	1993 Medicaid Limits	11.24*	7.81	0.38	7.39*	4.87*		3.84
	1989 Medicaid Limits	2919*	7.81	0.38	0.26	0.19		3.84
Primary Caregiver								
	1993 Medicaid Limits	27.57*	7.81	9.03*	0.66	0.27		3.84
	1989 Medicaid Limits	22019*	7.81	9.03*	3.14	1.36		3.84
Hours of Care								
	1993 Medicaid Limits	8.00*	7.81	0.16	5.17*	3.26		3.84
	1989 Medicaid Limits	34.00*	7.81	0.16	0.00	1.42		3.84
Wealth and interactions using 1989 Medicaid Limits with:								
Multiple Caregiver								
	Missing Wealth Observations Excluded	3874*	7.81	1.33	1.15	1.42		3.84
	Missing Wealth Observations Dummy Variable	51.92*	9.49	2.09	2.40	2.89	0.40	3.84
	Smoothed Limits with Missing Wealth Dummy	48.46*	9.49	2.41	0.03	0.74	0.29	3.84
	Average Wealth Smoothed Limits with Missing Wealth Dummy	70.93*	9.49	0.08	0.10	0.00	0.28	3.84
Primary Caregiver								
	Missing Wealth Observations Excluded	3177*	7.81	4.25*	1.51	2.06		3.84
	Missing Wealth Observations Dummy Variable	1261*	9.49	7.62*	6.50*	7.53*	0.01	3.84
	Smoothed Limits with Missing Wealth Dummy	375*	9.49	7.62*	5.81*	6.58*	0.01	3.84
	Average Wealth Smoothed Limits with Missing Wealth Dummy	236*	9.49	4.60*	4.27*	4.04*	0.16	3.84
Hours of Care								
	Missing Wealth Observations Excluded	3327*	7.81	1.82	0.52	0.64		3.84
	Missing Wealth Observations Dummy Variable	15.30*	9.49	3.27	2.11	2.52	1.49	3.84
	Smoothed Limits with Missing Wealth Dummy	15.29*	9.49	3.27	3.51	1.40	1.49	3.84
	Average Wealth Smoothed Limits with Missing Wealth Dummy	9.49*	9.49	2.98	1.29	0.08	1.15	3.84

Notes: The joint restrictions are on income (or wealth) and income (or wealth) interacted with Medicaid limits, the presence of a medically needy program, and a missing wealth dummy (when noted). * indicates test statistic is greater than the critical value. Critical values for joint tests with 2 and 3 degrees of freedom are 7.81 and 9.49. The critical value for one degree of freedom (for the individual test statistics) is 3.84.

Table 8: Income and Assets Lagrange Multiplier Tests

Table 8 presents the results of Lagrange Multiplier tests for each model specification. The top panel displays the results concerning income and its interactions, while the bottom panel displays the results concerning wealth and its interactions. For each specification, we conduct a joint chi-square test as well as separate chi-square tests for each restriction. Collectively, the results provide an inconsistent picture of whether including income or wealth and their interactions would improve the fit of the models. For the Multiple Caregiver Model, the results indicate that the fit would be improved by including income and its interactions with the 1993 Medicaid policy characteristics: the parameter estimates associated with income interacted with the presence of a medically needy program and income interacted with Medicaid income limits are individually and jointly statistically significant. However, in contrast to Gardner and Gilleskie (2009), the corresponding parameter estimates associated with 1989 Medicaid policy characteristics are not statistically significant. For the Primary

Caregiver Model, the parameter estimates associated with income and its interactions are jointly statistically significant for both years. While the parameter estimate associated with income is individually significant for both years, the policy interactions are not. Similarly, in the Hours of Care Model, income and its interactions with Medicaid policy are jointly significant for both Medicaid limit years. However, the interaction between income and the presence of a medically needy program in 1993 is the only variable with an individually significant coefficient. For all three models, the parameter estimates associated with wealth and its interactions are jointly statistically significant. An examination of the individual restrictions suggests that wealth and its interactions are individually related to the choice of the primary care arrangement (with two exceptions). In summary, we find weak and mixed evidence in favor of including measures of income and wealth even when interacted with Medicaid policy characteristics.

5.2 State-Specific Effects

Although our models include several market conditions and public policies in the elderly individual's or couple's state of residence, the models may not capture all state-specific/arrangement-specific or other state-specific effects. For example, other nursing home regulations, the supply of home health aides, or state-specific variation in cultural attitudes may influence families' care decisions. Accordingly, our next set of specification tests concerns the possibility of state-specific/arrangement-specific fixed effects. Using observations from states where there is more than one elderly household, we perform Lagrange Multiplier tests to test the null hypothesis of no state-specific/arrangement-specific fixed effects. In particular, we amend the baseline model in equation (1) to

$$y^*_{nijt} = X_{nit}\beta_j + Z_{njt}\gamma + \alpha_j y_{nijt-1} + \sum_s d_{is}\tau_{js} + \omega_{nijt},$$

where d_{is} is a dummy variable equal to 1 if and only if parent i lives in state s. Under the null hypothesis, $\tau_{js} = 0$ for all choices and all states s.[19] The vast majority of the individual score statistics are statistically insignificant, and there is no obvious pattern associated with those that are significant.

[19] We include only states where there is more than one observation.

Next we compare our state-specific/arrangement-specific score statistics for the two formal modes of care to 1997 utilization rates based on data presented in LeBlanc, Tonner, and Harrington (2000). We translate their data into log(nursing home utilization per 1000 individuals aged 70 or over) and log(number of Medicaid waivers per 1000 individuals aged 70 or over). After excluding states with missing score statistics and/or utilization rates and one outlier,[20] we use data from the remaining 31 states to compute the correlation coefficients between the score statistics and the utilization rates. For the Multiple Caregiver Model, the correlation coefficients are roughly 0.38 for nursing home care and 0.09 for formal home health care. The correlation coefficients are smaller for the other two models. These results assuage our concerns regarding home health care usage, and we find only weak evidence that state-specific characteristics not included in our models affect nursing home usage.

5.3 Geographic Distance

Geographic distance between elderly individuals and their adult children may be endogenous. For example, children may move closer to their parents or vice versa as their parents age or develop health problems. For families with at least one child, Table 9 presents the overall location transitions of children relative to parents based on the three possible responses in AHEAD/HRS: co-residence, living within 10 miles, and living more than 10 miles away. For each family size, the probabilities on the diagonals reveal strong persistence in geographic distance. For example, among families where the parent and child are initially at least 10 miles apart, the proportion later co-residing ranges from 0.008 to 0.029, depending on family size; similarly, the proportion later living within 10 miles ranges from 0.005 to 0.011.

Next we examine location transitions in response to increased caregiving needs. Table 10 displays location transitions among families where at least one child initially lives more than 10 miles from her parent(s) and subsequently co-resides with her parent(s). For each of these families, we follow all initially distant children who provide no care in the first year until one becomes the primary caregiver (if ever). Column (1) reports the proportion of children who transition to coresidence with the parent among families where the parent experiences

[20] We exclude Oregon because the value of log (utilization of nursing homes per capita 70 years or older) is 6 standard deviations below the mean, whereas all other states used are within one standard deviation.

an increase in the number of ADL problems. Column (2) indicates the proportion of those children from Column 1 who become the primary caregiver. Columns (3) and (4) indicate the comparable proportions among families where the parent experiences no change in the number of ADL problems. Under the null hypothesis that changes in child location are exogenous, we would expect the proportions in columns (1) and (2) to be small, those in columns (1) and (3) to be similar, and those in columns (2) and (4) to be similar. For families with one or two children, the proportions in the first two columns are statistically significantly larger than those that would be predicted by a model with the transition rates presented in Table 9. Also, for such families, the proportion of children who become the primary caregiver (Column 2) is statistically significantly larger than what would be predicted by a model where location transitions are exogenous. We find similar results corresponding to increases in the number of IADL problems. These results suggest that location transitions may be endogenous.

	Transition Frequencies			Transition Probabilities		
Child Location Relative to Parent	Co-resident	Within 10 Miles	Farther than 10 Miles	Co-resident	Within 10 Miles	Farther than 10 Miles
Origin of Child in Families with 1 Child						
Co-resident	158	5	2	0.958	0.030	0.012
Within 10 miles	20	529	0	0.036	0.964	0.000
Farther than 10 miles	20	6	657	0.029	0.009	0.962
Origin of Child in Families with 2 Children						
Co-resident	245	10	7	0.935	0.038	0.027
Within 10 miles	35	1459	1	0.023	0.976	0.001
Farther than 10 miles	46	31	2810	0.016	0.011	0.973
Origin of Child in Families with 3 Children						
Co-resident	194	14	4	0.915	0.066	0.019
Within 10 miles	15	1469	0	0.010	0.990	0.000
Farther than 10 miles	31	16	2894	0.011	0.005	0.984
Origin of Child in Families with 4 Children						
Co-resident	166	10	5	0.917	0.055	0.028
Within 10 miles	14	1099	0	0.013	0.987	0.000
Farther than 10 miles	16	15	2044	0.008	0.007	0.985

Table 9: Location Transitions

We observe a relatively small number of children moving from far to live with the parent or vice versa. We are concerned, because an adult child and an elderly parent may move closer together so that the child can take care of the parent as her health declines. In this case, location choice would be endogenous. Table 10 presents tests of the statistical significance of this phenomenon. For each family, all children who live farther than 10 miles and provide no care in year 1 were followed in each subsequent wave until one child became the primary care provider (if ever). Columns (1)-(4) present four measures of joint dependence regarding the proportion of children who initially live far but move in with a parent or vice versa. Column (1) contains the proportion where the parent or the child moves after an increase in ADL problems, and column (2) contains the proportion of those in column (1) where the child provides care. Columns (3) and (4) are analogous to (1) and (2) without an increase in parent ADL problems. Under the null hypothesis that child location transitions are exogenous, the proportions in columns (1) and (2) should be small, the proportions in columns (1) and (3) should be similar in size, and the proportions in columns (2) and (4) should be similar in size.

	Among Children Intially Living More than 10 Miles Away			
	After ADLs Increase		No Change in ADLs	
	Proportion who Coreside with Parent (1)	Proportion of Coresiding Children who Provide Care (2)	Proportion who Coreside with Parent (3)	Proportion of Coresiding Children who Provide Care (4)
Families with 1 Child				
Estimate	0.375	0.667	0.026	0.308
5% Critical Region	(0.023, 1.000)	(0.125, 1.000)	(0.000, 0.027)	(0.000,0.000)
Families with 2 Children				
Estimate	0.200	1.000	0.014	0.333
5% Critical Region	(0.003, 1.000)	(0.017,1.000)	(0.000,0.018)	(0.000,0.000)
Families with 3 Children				
Estimate	0.000		0.009	0.167
5% Critical Region	(0.007, 1.000)		(0.000,0.010)	(0.000,0.000)
Families with 4 Children				
Estimate	0.000		0.008	0.200
5% Critical Region	(0.006, 1.000)		(0.000, 0.006)	(0.000,0.000)

Notes: For this analysis, the parent is the father if he is alive and the mother otherwise. Critical regions were estimated under the null hypothesis by bootstrapping the distribution of these statistics.

Table 10: ADL Test Results for Primary Caregiver Model

For families with 1 or 2 children, the proportions in columns (1) and (2) are statistically significantly larger than what would be predicted in a model with location transition rates described in Table 9. Also, for such families, the proportion of children who become the primary care provider (Column 2) is statistically significantly larger than what would be predicted in a model where location transitions are exogenous. We find similar results for changes in IADLs. These results suggest that location transitions may be endogenous.

Therefore, we construct a likelihood-ratio test to decompose the effect of location into initial (exogenous) location and contemporaneous (possibly endogenous) location.

		Restricted Estimates			Unrestricted Estimates		
Child Location Relative to Parent		Estimate		Std Error	Estimate		Std Error
Co-resident	Initial	2.257	**	0.236	2.447	**	0.307
	Transition				2.281	**	0.321
Within 10 Miles of Parent	Initial	0.816	**	0.177	0.876	**	0.170
	Transition				0.891	*	0.488
Wald Test: Unrestricted Initial = Unrestricted Transition					0.276		(0.869)
Wald Test: Unrestricted Initial and Transition = Restricted Initial					0.318		(0.852)
Log Likelihood		-3085.4			-3058.6		
Likelihood-Ratio Test					53.8	**	

Notes: ** indicates significance at the 5% level; * indicates significance at the 10% level. The Wald Test of Unrestricted = Restricted is conditional on the restricted estimates. P-values are in parenthesis. The Likelihood-Ratio test statistic is distributed χ^2 with 2 degress of freedom under the null.

Table 11: Likelihood-Ratio and Wald Tests for Location Endogeneity

Recall that our original model captures the effect of location on care provision as:

$$z_{ikt6}\gamma_6 + z_{ikt7}\gamma_7,$$

where z_{ikt6} is a dummy variable that equals one if child k in family i lives within 10 miles of the parent in year t and z_{ikt7} is a dummy variable that equals one if child k in family i lives with the parent in year t. To further explore the possible endogeneity of location, we construct a likelihood ratio test to decompose the effect of location into two components: an initial, presumably exogenous location and a current, possibly endogenous component. Here we estimate a version of the Multiple Caregiver Model that specifies the effect of location on care provision as:

$$z_{ik16}\gamma_6 + (z_{ikt6} - z_{ik16})\gamma_{6a} + z_{ik17}\gamma_7 + (z_{ikt7} - z_{ik17})\gamma_{7a}.$$

Under the null hypothesis that the model is correctly specified, $\gamma_6 = \gamma_{6a}$ and $\gamma_7 = \gamma_{7a}$. Alternatively, if location transitions have a different effect on care than does initial location, then $\gamma_6 \neq \gamma_{6a}$ and $\gamma_7 \neq \gamma_{7a}$. As shown in Table 11, the likelihood-ratio test suggests that we should reject the null hypothesis that the model is correctly specified, but the Wald tests suggest we should not reject the null. However, the close proximity of the initial and transition parameters suggests that any endogeneity in location transitions would cause small bias (conditional on initial location being exogenous). Thus, as long as initial location is exogenous, we do not find strong evidence that current location is affected by potential endogeneity issues.[21]

6 Conclusions

We contribute to the long-term care literature by developing and estimating three dynamic models of families' care arrangements for the elderly. Our dynamic framework links care arrangements over time by allowing for true and spurious state dependence. Controlling for observable characteristics of the potential care recipients and the potential care providers and allowing for several types of unobserved heterogeneity, we isolate the impact of true state dependence. In theory, state dependence could be positive or negative, depending on the relative importance of caregiver burden and inertia. Our results provide strong evidence of positive state dependence in care arrangements. Thus, to the extent that caregiver burnout contributes to long-term care arrangements, its effects are dominated by inertia.

In addition, our results provide important policy implications. The effects of market conditions and public policies on the use of formal home health care and institutional care are smaller and less statistically significant in our dynamic model than in an otherwise identical static model. This pattern suggests that the measured effects in the dynamic model reflect flows while those in the static model reflect a stock of present and future flows. Nevertheless, even after allowing for state dependence, families' care decisions depend on the cost, quality, and availability of formal modes of care.

As an early step towards understanding the dynamics of long-term care arrangements, this work abstracts from the possibility that family members have different preferences. In future work, we plan to examine the strategic dimensions of long-term care decisions in a dynamic setting. In particular, we plan to develop and estimate a dynamic game-theoretic model by extending the static game-theoretic model developed in BGHS.

[21] We also tested whether location was endogenous in the Multiple Caregiver Model. The results are consistent with those presented here.

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