CENTER *for* RETIREMENT RESEARCH *at* BOSTON COLLEGE

NEW EVIDENCE ON THE RISK OF REQUIRING LONG-TERM CARE

Leora Friedberg, Wenliang Hou, Wei Sun, Anthony Webb, and Zhenyu Li

CRR WP 2014-12
Released: November 2014
Revised: October 2015

Center for Retirement Research at Boston College
Hovey House
140 Commonwealth Ave
Chestnut Hill, MA 02467
Tel: 617-552-1762   Fax: 617-552-0191
http://crr.bc.edu

Leora Friedberg is an associate professor at the University of Virginia. Wenliang Hou is a research associate at the Center for Retirement Research at Boston College (CRR). Wei Sun is an assistant professor at the Renmin University of China. Anthony Webb is a senior research economist at the CRR. Zhenyu Li is a former research associate at the CRR. The research reported herein was pursuant to a grant from the National Institutes of Health (NIH). The findings and conclusions expressed are solely those of the authors and do not represent the views of NIH, the University of Virginia, the Renmin University of China, or Boston College. The authors thank Siying Liu of the University of Virginia for excellent research assistance and Jeffrey Brown and Eric Stallard for their comments.

About the Center for Retirement Research

The Center for Retirement Research at Boston College, part of a consortium that includes parallel centers at the University of Michigan and the National Bureau of Economic Research, was established in 1998 through a grant from the Social Security Administration. The Center's mission is to produce first-class research and forge a strong link between the academic community and decision-makers in the public and private sectors around an issue of critical importance to the nation's future. To achieve this mission, the Center sponsors a wide variety of research projects, transmits new findings to a broad audience, trains new scholars, and broadens access to valuable data sources.

Center for Retirement Research at Boston College
Hovey House
140 Commonwealth Ave
Chestnut Hill, MA 02467
Tel: 617-552-1762 Fax: 617-552-0191
http://crr.bc.edu

Affiliated Institutions:
The Brookings Institution
Massachusetts Institute of Technology
Syracuse University
Urban Institute

Abstract

The expectation of needing long-term care is an essential input into optimal saving and long-term care insurance decisions. Previous optimization models have used the Robinson (2002) transition probabilities, which have not been systematically updated and which underpredict the use of care while overpredicting the average stay of people who enter care. We develop a new statistical model and use current data to estimate health impairment and care transition probabilities. We show that impairment and care use have declined and that, after incorporating the new transition probabilities, optimal long-term care insurance holdings are much lower and are close to actual holdings.

Introduction

Long-term care is one of the major expenses faced by many older Americans. Yet, we have only limited information about the risk or expected duration of needing home health care, assisted living or a nursing home.[1] Understanding expected long-term care costs is critical for several purposes: gaining a comprehensive understanding of Medicaid finances, since 29.5% of Medicaid funding in 2012 went to long-term care costs; analyzing optimal saving behavior by households preparing for old age; and explaining the long-term care insurance puzzle, since the use of insurance to shield against the risk of long-term care costs is surprisingly low.

Previous research has used the Robinson (2002) transition model, which shows the likelihood of transitioning from healthy to impaired states and how that affects the use of care, as based largely on *National Long Term Care Survey* (NLTCS) data for 1982-89.[2] The Robinson transition probabilities have been used by insurance companies to price long-term care insurance and by regulators to assess applications for premium increases. They have also been used by academic researchers modeling long-term care insurance purchase and post-retirement saving (Brown and Finkelstein 2008, Ameriks et al 2011). Although the Robinson model continues to be widely used, recent evidence suggests that those estimates are misleading, and the data upon which it is largely based are now 20-30 years old. We show why the results are misleading as well as the importance of using recent information. Then, we modify and update the Robinson care transition model. We estimate new transition matrices for monthly impairment and care states and make them available to the research and policy community.

New results in Hurd, Michaud, and Rohwedder (2013) prompt concerns about the Robinson estimates. Hurd, Michaud, and Rohwedder use data on nursing home use from the *Health and Retirement Study* (HRS), which has the advantages over the NLTCS of both exit interviews with relatives of deceased participants and an extremely long panel. Their analysis indicates that the Robinson model may substantially underestimate the probability of ever receiving care and correspondingly overestimate the mean duration of care conditional on admission – key differences in understanding the distribution of care costs. For example, the Robinson model predicts that at age 65 men and women have a 27 and 44 percent chance,

---

[1] Private long-term care insurers have information about their insurance pool, consisting of those who relatively wealthy and possibly adversely selected. Medicaid has information about those who are relatively poor.
[2] The model was estimated using 1982-89 data, and then ex post adjustments were made to capture some changing trends in care use through 1994.

respectively, of ever needing care. Hurd, Michaud, and Rohwedder estimate that at age 50 men and women have a 50 and 65 percent chance, respectively – substantially higher, even though they consider the population beginning at a younger age.[3] But, they also estimate shorter average durations of care conditional on admission, resulting from much shorter average stays in care, followed often by exits to the community.

Insurance companies and insurance regulators may be mainly concerned with the unconditional mean duration of care, which will affect claim costs. The existing model remains adequate for this purpose, subject to using updated data. But, researchers modeling the long-term care insurance purchase decision will be equally interested in the distribution of costs. If entry to a nursing home is a high-probability but relatively short-duration (and so lower-cost) occurrence, models that treat it as a lower-probability, higher-cost occurrence may overstate the value of insurance.

We first describe the HRS and NLTCS datasets and how they report impairment and care use. We show that impairment and most use of care have declined since the early 1980s. While the Robinson (2002) model captures the recent unconditional mean duration of nursing home stays, specific design features that we identify in the statistical model result in a substantial overestimate of the conditional mean duration of stays and a correspondingly substantial underestimate of the risk of ever entering a nursing home, even compared to recent lower rates of care use. We use the NLTCS and HRS to estimate the full set of transitions across health impairment and across long-term care states unconditionally and conditional on health, by gender and age. The key difference in our approach is to match numerous moments of nursing home use in order to quantify the actual churn in and out of nursing homes. Patterns of life-time care utilization based on our model differ substantially from Robinson's and closely match the utilization rates reported in Hurd, Michaud, and Rohwedder (2013).

Lastly, we show that use of our new transition probabilities in a model of optimal wealth decumulation substantially reduces willingness to pay for long-term care insurance relative to values obtained using the Robinson model, for example in Brown and Finkelstein (2008). This occurs both because the expected present values of benefit payouts fall and premiums rise,

[3] Individuals who die between the ages of 50 and 65 are less likely to use care before death than are people who die at older ages.

[4] This should be viewed as an upper bound on the possible crowd-out effect of Medicare. Many but not all initial stays in nursing homes qualify for Medicare, but neither the HRS nor NLTCS allow us to quantify which nursing home stays are Medicare-eligible.

reducing the money's worth of observed policies; and because the risk of extreme care costs falls. Our estimates further suggest that Medicaid participation will be higher than projected when using the Robinson estimates, while average Medicaid costs per participant will fall, leaving overall Medicaid costs little changed. Meanwhile, willingness-to-pay is further reduced (perhaps leaving no single men willing to purchase insurance) when we also incorporate Medicare payments for the first 100 days of initial nursing home stays.[4] This demonstrates another contribution of our new transition probabilities, as even the HRS does not provide a clear picture at the monthly level to shed light on the role of Medicare. Social insurance crowd-out from Medicaid and also Medicare is thus an even stronger explanation for the low level of long-term care insurance coverage than previously thought.

The remainder of this paper is organized as follows. Section 1 summarizes previous research, focusing on the work of Robinson (2002) and Hurd, Michaud, and Rohwedder (2013). Section 2 compares the HRS and NLTCS data. Section 3 describes the Robinson model. Section 4 explains how we modify it to match moments of lifetime care histories in the HRS data. Section 5 presents results and Section 6 concludes.

1. Previous Research

Previous studies of the incidence of nursing home utilization include Liang, Tu, and Whitelaw (1985), Cohen, Tell, and Wallack (1986), Kemper and Murtaugh (1991), Arling Hagan and Buhang (1992), Dick, Garber and MaCurdy (1994), Robinson (2002), Spillman and Lubitz (2002), Kelly et.al. (2010), Hurd, Michaud, and Rohwedder (2013), and Fong, Shao, and Sherris (2013). The Robinson (2002) model differs from the other papers in that it yields not only estimates of the distribution of the length of lifetime care use, but also monthly care status transition probabilities. The Robinson transition probabilities enable researchers to model the risk of not merely being unable to pay nursing home bills, but also of being discharged to the community shorn of one's wealth. The transition matrices have been utilized by Brown and Finkelstein (2008) and Sun and Webb (2013) to calculate optimal long-term care insurance

[4] This should be viewed as an upper bound on the possible crowd-out effect of Medicare. Many but not all initial stays in nursing homes qualify for Medicare, but neither the HRS nor NLTCS allow us to quantify which nursing home stays are Medicare-eligible.

purchase and post-retirement wealth decumulation.[5] The focus on monthly intervals is particularly valuable because the HRS data show that many individuals experience multiple short nursing home stays that would not be captured in a model that estimated care transitions at annual intervals. The model is highly regarded; Brown and Finkelstein (2004) report that it "has a very strong pedigree," being used by "insurance regulators, private insurance companies, state agencies, state agencies administering public long-term care benefit programs, and the Society of Actuaries LTC Valuation Methods Task Force."

Table 1 summarizes key data sources and findings on the use of care from the above papers. Prior to Hurd, Michaud and Rohwedder (2013), estimates of the risk of ever requiring care clustered within a narrow range. The most widely cited papers are Kemper and Murtaugh (1991) and Dick, Garber and MaCurdy (1994). Kemper and Murtaugh estimate that 33 percent of men and 52 percent of women turning 65 in 1990 will ever require nursing home care.[6] Yet, using the HRS, Hurd, Michaud, and Rohwedder report estimates of the probability of ever requiring care of 50 and 65 percent for men and women, respectively, at age 50, much higher than previous estimates that were conditional on attaining age 65.[7] Meanwhile, they obtain much lower estimates of the mean duration of care conditional on entry, so their estimates of unconditional mean durations of care are actually similar to those obtained previously. The unconditional mean durations of care are 0.35 and 0.88 years for men and women respectively in Robinson and 0.48 and 0.73 years in Dick, Garber and MaCurdy, compared with 0.35 and 0.78 years for the parametric estimate in Hurd, Michaud, and Rohwedder.

Hurd, Michaud, and Rohwedder discuss potential explanations for their much higher rate of nursing home utilization. First, they rule out changes over time by showing that there has been little overall trend in the prevalence of nursing home use in the HRS over the past 12 years,

[5] The model can also be applied to other household decisions that may be affected by health or care status. Reichling and Smetters (2013) use Robinson estimates of health transitions in an analysis of optimal annuity purchase.

[6] A puzzling feature of Dick, Garber, and MaCurdy is that, in contrast to the finding in all the other studies that women are at much higher risk, their results suggest that men and women are almost equally likely to ever need care, at 36 and 35 percent. The probabilities of entering care can be computed by comparing the conditional with the unconditional mean durations of stay. Unlike the other papers, Fong, Shao, and Sherris (2013) focus on transitions between being non-disabled, functionally disabled, and dead, and do not distinguish between requiring home health and nursing home care. Using HRS data, they estimate the lifetime incidence of disability at age 65 and over at 37 percent for men and 54 percent for women.

[7] They produce non-parametric estimate that are very similar, at 53 percent for men and women combined. Our analysis of the HRS shows that those who die before age 65 are less likely to use nursing home care than those who die after age 65 and that few of those who do not use care after age 65 use care between 50-64. So, the probability of using care conditional on attaining age 50 is likely lower than the probability conditional on attaining age 65.

while our analyses of NLTCS data, discussed later, show that age-specific institutionalization rates have declined (not risen) over the longer term. A second possible explanation is that the HRS exit interviews provide an accurate picture of nursing home use in the last two years of life, in contrast to some other studies that either lack or have possibly lower-quality exit interviews.[8] But, Dick, Garber, and MaCurdy find a much lower percentage using nursing homes in the 1982-84 NLTCS, and the 1984 NLTCS exit interviews ask almost identical questions to those in the HRS and use an almost identical recall period.[9] A third explanation considered by Hurd, Michaud, and Rohwedder is that the methodology used by Dick, Garber, and MaCurdy to combine the NLTCS surveys results in a sample that is unrepresentative of the population. This explanation is immaterial to us, as we focus on the Robinson (2002) model.

As we will show, a fourth explanation can account for the differences between the Robinson and the Hurd, Michaud, and Rohwedder estimates. We argue that the Robinson model suffers from design features that lead it to overestimate the conditional mean duration of stay and underestimate the probability of entry. Specifically, the mechanism used to assign individuals to care does not allow for sufficient churn, so that too many individuals in the model either enter care and remain there until death or never enter care.

At the same time, Manton and Gu (2001) and Manton, Gu, and Lamb (2006) find that the prevalence of chronic disability declines during the course of the NLTCS. Although Hurd, Michaud, and Rohwedder find little trend in long-term care utilization from 1996 onwards, Manton, Gu, and Lamb show a near halving of institutionalization rates from 1982 to 2004. The Robinson model was estimated using only 1982-89 data but then captures those trends by adjusting the estimates with ex post age-specific multiplicative factors and in other ways to approximate the probability of nursing home entry through 1994.

[8] An example of the importance of exit data is apparent when considering the estimates of the lifetime risk of functional disability in Fong, Shao, and Sherritt (2013). As almost all nursing home residents are functionally disabled, but some functionally disabled individuals live in the community, the lifetime risk functional disability should be higher than the Hurd, Michaud, and Rohwedder (2013) estimates of the lifetime risk of entry to a nursing home. We hypothesize that the omission of exit data explains why the estimates are somewhat lower.

[9] Furthermore, as mentioned above, Dick, Garber, and MaCurdy report almost identical unconditional mean durations of stay to those in Hurd, Michaud, and Rohwedder, suggesting that they are doing a good job of capturing stays in the last years of life. Recall bias might explain the low utilization rates in Kemper and Murtaugh (1991), which are based on the 1986 Mortality Followback Survey in which respondents are asked about lifetime care use of deceased relatives. This survey will understate lifetime use to the extent that the respondent is either unaware of or does not recall stays. But, mean durations of stay in this study are also close to those in Hurd, Michaud, and Rohwedder, casting doubt on this hypothesis.

This underlines the need to use updated data. Therefore, we combine recent information from both the NLTCS and the HRS when modifying the Robinson model. We continue to use the NLTCS supplemented with the 1999 and 2004 waves and allowing for time trends in order to estimate health status transitions, the first of two key ingredients to the care transition model. Our decision was motivated by three considerations. First, by continuing to use the NLTCS, we can show to what extent the changes in health status transitions reflect true changes rather than a shift in the survey method. Second, the NLTCS permits a more nuanced understanding of the ability to perform activities of daily living (ADLs) than does the HRS. This aligns with insurance company policies that condition long-term care benefit eligibility on both care use and difficulties with performing an ADL. Third, the 2004 NLTCS asks specifically about assisted living facilities, permitting a more accurate categorization than the HRS does. Meanwhile, we use the HRS to characterize patterns of lifetime utilization of nursing homes, rather than the NLTCS as in Robinson. The HRS offers a long panel, detailed questions on separate care episodes, and exit interviews that report care in the final months of life.

A final point about the previous literature affects our use of the care transition matrix to determine crowd-out from social insurance. The calculations of willingness-to-pay for long-term care insurance in Brown and Finkelstein (2008) and Sun and Webb (2013) do not account for Medicare payments for the initial period of many nursing home stays. The resulting overstatement of willingness-to-pay could be material, as Medicare paid for up to 25.2 percent of all nursing home costs in 2011.[10] We can use our care matrix to gain much more insight about stays that may qualify for Medicare than is possible using the HRS.

2. Data

We use the NLTCS to estimate a transition matrix in health impairment states that affect the need for care and then match predicted care states as a function of health to care states observed in the HRS (for nursing home care) and NLTCS (for assisted living and home health care). As noted earlier, the NLTCS offers more information on health, while the HRS offers information about nursing home spells and returns to the community for a long panel.

[10] This figure is an upper bound from Centers for Medicare and Medicaid Services (2013), Table 13, which does not reflect the individual co-pay.

The Health and Retirement Study

In this section we show HRS statistics about nursing home use and compare them to predicted nursing home use from the Robinson model. We use the Health and Retirement Study (HRS) to examine nursing home use for a panel of representative older Americans. At every interview, participants, or in the case of exit interviews, relatives of deceased participants, were asked whether they had a nursing home stay, the number of stays and the number of nights spent in a nursing home since the previous interview; and whether they were living in a nursing home at the date of the interview or died (asked only in exit interviews) while in a nursing home. In spite of the level of detail, answers on month-by-month care are too incomplete and/or inconsistent to use systematically. Rather, we simulate monthly care transition probabilities as a function of monthly health transition probabilities so that numerous simulated care statistics match those observed in the HRS, based on the questions above, and the NLTCS.

The HRS follows Americans aged 51 and older.[11] Two issues keep the HRS from being fully representative: the HRS begins with a non-institutionalized population, and it does not yet reveal lifetime care histories. To deal with the first problem, we begin computing care statistics at the third wave after cohort entry, as suggested by Hurd, Michaud, and Rohwedder (2013). They show that by the third wave, institutionalization rates by age are at the same level as in subsequent waves for cohorts who entered the survey at younger ages, presumably because those who were institutionalized at baseline and who were therefore excluded from the survey have mostly died. They infer that by then the sample is representative of the population. We also follow them by assigning the last non-zero weight given to respondents who were institutionalized, as the HRS assigns them a zero survey weight for aggregation purposes.

To deal with the second problem, we link together people in different HRS cohorts to impute full care histories from age 65 on; the key assumption is that health influences care in the same way for each cohort. Most of the 1931-41 cohort, who were 51-61 in their first interview in 1992, were still alive at the 2010 interview, when they were aged 69-79. Those born before 1924, who were 70 in their first interview in 1993, are mostly deceased by 2010. We follow a similar procedure as Hurd, Michaud, and Rohwedder to address these left- and right- censoring

[11] The original HRS sample has been interviewed every two years since 1992 and comprises individuals aged approximately 51-61 (born between 1931 and 1941) and their spouses. In 1993, the AHEAD sample of individuals aged 70 and over (born before 1924) joined the survey and were re-interviewed in 1995, 1998, and every two years thereafter. Those born 1925-30 and 1942-47 were added in 1998, and younger individuals were added in 2004 and 2010. These cohorts have not been observed for a long period and hence are not used for our analysis.

problems, arising because the past care utilization of participants who joined the panel after age 65 and because the future care utilization of participants who joined the panel at younger ages and have not yet died are unobserved. They begin by focusing on the cohort aged 70-74 in 1993 and use older cohorts to fill in their end-of-life care history and younger cohorts to fill in their early-old-age care history.[12] They arrive at an overall probability of using care after age 50-54 of 53.6 percent. The resulting rates of nursing home use overall and by age cohort are substantially higher than the rates from Robinson (2002).

A potential concern is that the probability of entering care may be correlated with prior episodes of care.[13] We account for possible correlation by using multiple hot-deck imputation (Rubin 1987) to splice together individuals with similar nursing home use across ages in order to impute complete nursing home histories that incorporate correlations across care episodes. Our starting point is AHEAD individuals born between 1919-1923 and aged 75-79 in 1998 (recall that we drop individuals in the first two waves because the sample begins with only those who are not institutionalized) and who, if they survived to 2010, were aged 87-91. We splice them with HRS individuals born in 1931-1935, who were turning 65 between 1996 and 2000 (when we first observed them) and who were 75-79 in 2010. We also splice HRS survivors with AHEAD participants born 1907-1911, who were aged 87-91 in 1998 and, had they survived, would have been aged 99-103 in 2010, so as to impute care histories at ages beyond 87-91.[14] Only 19 AHEAD participants attained those ages in 2010, so this procedure yields an essentially complete history from age 65. Our multiple hot-deck uses age, gender, marital status, number of ADL limitations, and current nursing home status to join people with similar characteristics. Finally, we add to the sample individuals who were observed at age 65 but died by ages 75-79.

---

[12] To give an example, they calculate the percentage of the cohort aged 70-74 in 1993 who died by 2010 and the percentages among the deceased and the survivors who utilized care between 1993-2010, and the same for the cohort aged 87-91 in 1993. Assuming that the probability of using care after ages 87-91 is uncorrelated with the probability between 70-74 and 87-91 and that the relationship between health status and care needs has not changed (and they show that overall care use does not trend substantially during the HRS), they estimate the lifetime probability of using care conditional on surviving to ages 70-74 by multiplying out the above probabilities. By 2010, 33 percent of those aged 70-74 in 1993 were still alive. Between 1993-2010, 29 percent of survivors and 49 percent of the deceased ever used care. Among those aged 87-91 in 1993, 65 percent ever used care. The probability of using care after age 70-74 thus equals (0.67*0.49)+(0.33*(0.29+(0.71*0.65))), or 57.6 percent.

[13] If it is positively correlated, their approach will overstate lifetime risk for the average individual because many observed spells will be repeat spells for a relatively small number of individuals. Conversely, if it is negatively correlated, it will understate lifetime risk, because not having experienced a spell will raise future risk of a spell.

[14] Our care utilization rates are therefore representative of the period from 1998 onwards, rather than of any particular birth cohort. We ensure that the weighted number accords with the predicted number of survivors obtained from Social Security Administration mortality tables for the relevant birth cohorts.

Table 2 compares sample statistics derived from our spliced HRS lifetime nursing home utilization histories with statistics obtained from simulations of the Robinson (2002) model and reported in Brown and Finkelstein (2004). Our unconditional mean durations of care are similar to those of Robinson, with values for men of 0.35 years in Robinson and 0.37 in the HRS. But, our probabilities of entering a nursing home are much higher than those of Robinson (27 percent in Robinson and 44 percent in the HRS, for men), and our conditional mean durations of care are correspondingly much lower (1.30 years for Robinson and 0.85 in the HRS). Our pooled average probability of entering care of 52 percent is slightly lower than the Hurd, Michaud, and Rohwedder non-parametric estimate of 53 percent, and we estimate slightly higher conditional means for both men and women.[15]

The National Long-Term Care Survey

We use the NLTCS to estimate a transition matrix in health states, defined by physical and cognitive impairment, that affect the need for care as defined by insurers.[16] We will then match care states as predicted by health to nursing home use observed in the HRS and other care use observed in the NLTCS. In this section, we discuss how we use the NLTCS data on health and on care and then observe trends in health and care use.

The National Long-Term Care Survey is a nationally representative survey of Medicare beneficiaries aged 65 or over. It is a panel survey that interviewed participants in 1982, 1984, 1989, 1994, 1999, and 2004. The NLTCS takes steps to maintain a representative sample and also obtain information about the deceased, as described in the Appendix. The 1982 survey began with 20,485 individuals. About 5,000 people die between waves and are replaced by a sample of about that size who attained age 65 subsequent to the previous wave.

The NLTCS asks detailed questions about cognitive and physical limitations. Robinson (2002) characterizes the need for care as a function of both cognitive impairment as reported directly and physical impairment as captured by need for assistance with Activities of Daily Living (ADLs) and Instrumental Activities of Daily Living (IADLs). This reflects the goal of

[15] We precisely replicated their mortality and nursing home utilization rates for the period 1993-2010 for individuals aged 70-74 in 1993. Note also that the HRS probability of entering care in Table 2 is *higher* than the value obtained as an output of the Robinson statistical model, even though cross-sectional comparisons of the recent HRS and the early NLTCS, shown later, reveal long-term *declines* in the probability of being in care at all ages. This highlights how the Robinson model overestimates lifetime care use, while underestimating the unconditional duration of use.
[16] The HRS does not report the level of detail about impairment that would allow us to approximate the care needs that trigger insurance benefits.

the model, which serves as a pricing tool for insurance company actuaries and regulators. Policy benefits are triggered by need for care as defined by ADL status, and insurance companies anticipate that almost all eligible individuals will claim benefits. Following Robinson, we model transitions among states of worsening health, but based on our analysis and comparisons across data sets that are described in the Appendix, we modify how ADLs and IADLs are used to define health states. For example, Robinson's definitions results in both a high and increasing number of individuals experiencing limitations with IADLs, which seems unrealistic, and also in substantial declines in ADLs over time, in disagreement with other authors.

After settling on thresholds for IADL and ADL limitations, we follow Robinson in defining seven states of progressively greater impairment: well (no cognitive impairment and able to perform all ADLs and IADLs); unable to perform 1+ IADL but able to perform ADLs; no cognitive impairment but unable to perform 1, 2, or 3+ ADLs; or cognitive impairment and unable to perform <2 or 2+ ADLs.[17]

Trends in Health and in Care Use

Table 3A reports the percentages of NLTCS participants in each of these seven impairment states by age group in 1984 and 2004. The upward trend in wellness at all ages is apparent in Figures 1A and 1B for men and women, respectively, consistent with previous research. Age-specific disability rates declined over the period, more so for the oldest old. For example, the share of the sample who are well (no IADL or ADL limitations) is 54.2 percent for men aged 85-89 in 1984 and 68.2 percent in 2004, while it was 42.0 percent for women of the same age in 1984 and 55.6 percent in 2004.[18] The improvements for men in degree of impairment are almost across the board, with reductions in limitations on IADLs and ADLs but with increased cognitive impairment at ages 85 plus. The declines in impairment for women are smaller, with decreased cognitive impairment but a slight worsening in ADL limitations.

[17] The detailed classification mimics how long-term care insurance is priced. Insurers typically place ADLs in 5-6 categories and pay benefits if someone cannot perform 2+ (Department of Health and Human Services, 2015).

[18] These rates are comparable to those found by others using different data and methods. For example, Murtaugh et al. (1995) estimate that 12 to 23 percent of 65 year olds are so impaired as to be ineligible to purchase insurance.

Table 3B similarly reports the use of home health care, assisted living, and nursing homes, by age, in the 1984 and 2004 NLTCS.[19] Figures 2A and 2B emphasize the decline in nursing home use for men and women, respectively. The share living in a nursing home is 11.8 percent of men aged 85-89 in 1984 versus 5.9 percent in 2004, and 22.4 percent of women in 1984 versus 14.9 percent in 2004. The overall rate of nursing home use at ages 65 and over declined 40 percent.[20] In results that are not shown, we find that the propensity to be in a nursing home conditional on the level of impairment fell only a little, so most of the decline in nursing home use occurred because of reduced impairment. Notably, this was not matched by an overall substitution towards home health care, which stayed relatively flat overall as the rate of severe impairment declined but the propensity to use home health care among those who were less impaired rose.[21] The share in assisted living declined at younger ages and rose at older ages.

Lastly, we note that the 2004 HRS and 2004 NLTCS report very similar cross-sectional rates of nursing home and assisted living utilization when excluding the HRS exit interviews to augment comparability. This is detailed in the Appendix and increases our confidence when we combine information from both surveys in order to update the Robinson model.

3. The Transition Model

Robinson (2002) produced a widely used transition matrix indicating the likelihood of moving among care states. The Robinson model has two parts. The first part uses three adjacent waves of the NLTCS (1982, 1984, 1989) to fit a likelihood model that estimates health transition probabilities. The second part uses two waves (1984, 1989) to estimate care status transition probabilities conditional on health and then makes ex post adjustments using other data.[22] We similarly develop a two-part model rather than using a single data set because, in our case, health is observed much better in the NLTCS and lifetime nursing home use is observed much better in

[19] Recall that we use the NLTCS to generate statistics on use of assisted living and home health care, and while we use the HRS to compute nursing home use, we can generate cross-sectional care use in the 1984 and 2004 NLTCS to reveal long-run trends. Our classification of these variables is described in the Appendix.
[20] The 2004 numbers aggregate to 1.21 million, somewhat lower than the 1.32 million reported in Table 6 of U.S. Department of Health and Human Services (2009), based on National Nursing Home Survey data for the same year.
[21] As we explain later, our care use model focuses on home health care that is used when impairment is relatively high, because that is what Medicaid or private insurance pays for. Thus, the trend toward greater use of home health care use among the less impaired will not affect our care use expectations.
[22] Robinson (2002), in fact, only describes the health transition model. Although it is not described in print, he has also made available the care transition model, which uses the health transition model as an input. Other data sources used to adjust the care transition model are the 1994 NLTCS data and the 1985 National Nursing Home Survey data.

the long HRS panel. We first describe our health transition model, which is similar to Robinson's but uses more waves of data (while allowing for time trends in the estimation because of the improvement in health noted above) and classifies individuals into health states a little differently. Then, we describe Robinson's care model and our alternative approach to modeling care status transition probabilities. Our major change is that we simultaneously match many statistics characterizing nursing home entry and exit; this allows our simulated data to match the degree of churn observed in nursing home use in the HRS.

Robinson omits, as do we, possible behavioral factors that influence the demand for care, independent of impairment. For example, we do not include marital status or the proximity of adult children; while these affect care-giving arrangements, as shown by Byrne et. al. (2009), Hiedemann et. al. (2013), and Pezzin and Schone (1999), they are not used to determine claims for long-term care insurance policies. Also, Costa Font and Courbage (2014) show that the availability of informal care may complement purchases of long-term care insurance by households who care about the quality of life of their potential care-givers. Meanwhile, the empirical importance of available family members may reflect at least in part the impact of socioeconomic status on care, but modeling this relationship is considerably more complicated, especially with limited data from the NLTCS on wealth or income.

The Health Transition Model

The first step is to use our definitions from above to classify NLTCS individuals into one of eight health states, as in Robinson: 1) well, 2) able to perform activities of daily living (ADLs) but unable to perform one or more instrumental activity of daily living (IADL), 3) not cognitively impaired but unable to perform one ADL, 4) not cognitively impaired but unable to perform two ADLs, 5) not cognitively impaired but unable to perform three or more ADLs, 6), cognitively impaired and unable to perform zero or one ADLs 7) cognitively impaired and unable to perform two or more ADLs, and 8) dead.   The second step is to cross-tabulate health states in each pair of adjacent waves (1982-84, 1984-89, and so on) to generate health transitions by age group (65-74, 75-84, and 85 plus) and gender, a total of six categories.[23]

[23] The NLTCS enables researchers to identify health status at the date of the interview but not when health status changed or when other health states occurred between interviews; this is why the data are collapsed in this way. The maximum likelihood estimation yields health transition probabilities that best fit the pattern of transitions from one interview date to the next. As previously mentioned, the NLTCS oversamples institutionalized individuals. We

We use maximum likelihood to estimate health transition probabilities as a function of age and gender (as in Robinson) and also time. Each matrix contains a total of 56 probabilities (for seven initial states and eight terminal states). The model takes the following form:

$$r_{i,j}(s,x,y)=\exp\left[a_{i,j}+b_{k\in\{i,j\}}(s-0.5)+c_{k\in\{i,j\}}\frac{x-80}{100}+d_{k\in\{i,j\}}(y-1982)+\varepsilon_{i,j}\right] \tag{1}$$

where $r_{ij}(s,x,y)$ is the annual rate of transition from status i to status j for an individual aged x of gender s in year y. We assume that ε_{ij} is distributed normally. No constraints are placed on the 49 values of a_{ij}, the likelihood of a transition for the base case.[24] As in Robinson, we constrain the other parameter values to be the same for broad types of health transitions in order to reduce dimensionality. The gender adjustment parameter $b_{k\in\{i,j\}}$ takes three values, one value for k such that $i>j$, recovery to a better health status; one for j=8, death; and one for other combinations of i and j that involve equal or worse health but not death. These adjustment parameters allow the baseline probability to differ for men and women when considering improvements compared to deterioration and when considering mortality. The age slope parameters $c_{k'}$ take five values, including the three that were used for the gender adjustment as well as separate values for transitions from healthy to dead and from healthy to other health states.[25]

We add more years of NLTCS data to the estimation, compared to Robinson, so it is important to control for the secular changes in health that we observe. Ideally, we would estimate the model separately for each year, allowing all the a_{ij}, b_{ij}, and c_{ij} coefficients to vary over time. We find that the estimated parameter values are unstable, and instead we include the d_k linear time trend, the slope of which is allowed to differ for mortality, improving health, and all other transitions, as for the b_k terms. The time trend has an important effect. Our health care status simulation shows that, based on only 1984 transition probabilities, 16.9% of men aged 65 would be healthy at age 85, and 67.4% would be dead at age 85. Based on 2004 transition

---

adjust for this by constructing transition weights. We obtain NLTCS mortality data that permit us to identify each participant's vital status and date of death. We adjust the cross section weights to reflect the possibility that an individual who was alive at both time t and t+5 may not be interviewed at $t+5$, whereas all deceased individuals will be included in the $t+5$ sample.

[24] The a_{ij} terms are estimated for transitions to states $i\neq j$, so there are terms for the transitions from the seven initial states to seven different terminal states, yielding 49.

[25] We follow Robinson in assuming that the 1984 survey was administered exactly two years after the 1982 survey and that the 1989 and subsequent surveys were administered at five-year intervals. The actual interval between the 1982 and 1984 surveys varied from one year ten months to two years and two months.

probabilities, 21.0% would be healthy and 63.7% dead, so the probability of being in good health is higher and the probability of death is lower.[26]

Concerns with the Earlier Care Status Transition Model

We take a more systematic approach to relate health transitions to care transitions than does Robinson, who makes specific adjustments in order to replicate features of the data. The major differences result from the treatment of nursing home use, where we have identified problems in the statistical model which lead to misleading estimates of conditional mean durations in care. We also make use of the HRS for nursing home information, which provides more moments to match than can the NLTCS.

To translate health transitions into care transitions, Robinson first simulates a large number of month-by-month health status histories. By construction, the percentages of individuals in each health status at each age match the underlying data. Then, he models use of different types of care conditional on health status in steps, beginning with nursing home care. In each step, he estimates the probability of being in that care state given age, gender, and health status using a logistic regression. Then, he assigns care status to each simulated individual each month by drawing a number from the uniform [0,1] distribution to serve as their permanent threshold. As long as this threshold exceeds the propensity for the individual's age, gender, and health status, the individual is deemed to remain in the community. Once the care use propensity increases to a level above one's threshold (due to aging or worsening health), the simulated individual is deemed to be in that care state. An improvement in health can lead to exit from that care state. The numerous simulated paths are tabulated to yield probabilities. This is done first for nursing home use and then similarly for assisted living, as described in the Appendix, while for home health care Robinson assumes that everyone with ADL limitations who is not in a nursing home or assisted living uses home health care.

Matching the appropriate "churning" in and out of nursing homes is the key problem that we have identified in the Robinson model. As health status typically worsens with age, the Robinson model described above would return few individuals to the community. In practice, some individuals return, even if impairment does not lessen. For example, individuals may be

[26] The age-weighted transition probabilities, when applied to 1999 NLTCS data, yield weighted five-year mortality rates that are almost identical to those in cohort mortality tables (69.4% for men and 62.1% for women). Note that our monthly probabilities of health transitions equal one-twelfth of the annual estimated probabilities.

institutionalized to provide respite for informal caregivers, or after a period of hospitalization. Robinson incorporates a duration adjustment factor, described in the Appendix, that increases the probability of institutionalization after the onset of disability and decreases it for individuals who have remained in the same disability state for a long period of time. But, these adjustment factors are ad-hoc.[27] Based on the discrepancy with Hurd, Michaud, and Rohwedder, they yield an inadequate degree of churning, and our use of additional statistics representing durations as well as utilization rates addresses this.

Our Care Status Transition Model

While we follow similar steps to Robinson in determining the care transition probabilities for each type of care sequentially, we begin with a systematic model of nursing home use that simultaneously matches many statistics characterizing nursing home entry and exit, rather than using a logistic regression to estimate the probability of being in a nursing home and then making ex post adjustments. This allows us to replicate not only the unconditional mean duration of nursing home care, but also the patterns of entry into, stays in, and exits from care.

The first step in the calculation, similar to Robinson, is to simulate 100,000 health status histories, based on our estimated health transition matrix. The second step is to create a 4x5 care transition matrix for each age and for each of the 56 (7x8) health transitions. There are four care states possible at time t (in community, eligible for home health care, in assisted living, in nursing home) and five care states at time $t+1$ (the four above and deceased), along with seven health states at time t and eight health states at time $t+1$ (including deceased). In principle this would require us to estimate an unfeasibly large total of 56*4*5=1120 age-varying probabilities. In reality, many of these transition probabilities are determinate. Consider, for example, someone who transitions from the health state in which he has two ADLs to the health state in which he is dead. We require that the initial care state cannot be "well" or "dead," as this is implied by the definition of ADLs, and that the individual similarly transitions from these care states to care state "dead" with probability one. Other transitions can never occur. For example, someone in health state "well" at time t can only be in care state "well". On the other hand, analysis of both HRS and NLTCS data reveals that some are in a nursing home even though they

[27] As noted earlier, Robinson adjusts the estimates by multiplying the probability of nursing home entry by ex post age-specific factors to capture changing trends in nursing home use through 1994.

report only having one ADL.[28] While this may reflect errors in reporting ADL status, rather than attempting to correct ADL status we allow individuals with only one ADL to enter nursing homes. Overall, we need to estimate 411 conditional transition probabilities.[29]

Now, focusing on specific care states, the third step is to determine the probabilities of entering or remaining in a nursing home between time t and $t+1$. We calibrate the probabilities by minimizing the weighted distance between the moments characterizing the distribution of nursing home care utilization in the HRS data and the corresponding moments in simulated care histories. These simulated care histories are created by applying the care status transition probabilities to the simulated health status histories.

In order to replicate the full set of transitions in and out of nursing home care, we match the following statistics on care transitions in the HRS:

- probability of ever using nursing home care
- average age of first use, conditional on use
- conditional average number of years spent in care
- conditional probabilities of using care for more than 1, 2, …, 7 years
- probability of nursing home entrants returning to the community
- probability of nursing home entrants having only one, two, or three stays.[30]

These include the eight statistics used in Ameriks, Caplin, Laufer, and Van Nieuwerburgh (2011) in their study of post-retirement saving and that we showed in Table 2. We add further statistics to capture the full distribution of durations and the likelihood of multiple stays. We compute these statistics using our spliced panel of HRS participants, split by gender, for ages 65 onward.

The model that we use to match these statistics assumes that the probability of entering a nursing home is zero when the individual is in health states 1, 2, or 8 at t+1 and greater than zero when in health states 3, 4, 5, 6, or 7 at $t+1$. The probability of entering a nursing home if not

---

[28] As mentioned previously, the ADL questions in the HRS are less detailed than those in the NLTCS. We assigned predicted probabilities of cognitive impairment using data available on the HRS website, supplemented by predicted probabilities for other waves generously supplied to us by Michael Hurd of RAND. Few of the institutionalized individuals with only one ADL limitation suffered from cognitive impairment.

[29] Of the 56 health status transitions, care status is pre-determined for 21. For the other 35, some of the 20 care transitions are not possible. There are 4 possible transitions in 10 cases and 14 possible transitions in 25 cases.

[30] This last statistic, which is important for capturing churn into and out of care, differs from Ameriks et al., who use the conditional mean number of spells. Recall that we cannot use moments that directly relate health and care use because we use different data sets to measure health (which is reported more precisely in the NLTCS) and lifetime nursing home use (which requires the HRS).

already in one is assumed to depend solely on age and on health status at times *t* and *t+1*, not on care status at time *t*.[31] We model the probability of entry to a nursing home as

$$\frac{1}{1+e^{-(\beta_3 h_3+\beta_4 h_4+\beta_5 h_5+\beta_6 h_6+\beta_7 h_7+\beta_8 ADL+\beta_9 CI+\beta_{10}(AGE-65))}} \qquad (2)$$

where h_3 h_4 h_5 h_6 h_7 indicate that the individual is in health states 3, 4, 5, 6, or 7 at time *t+1*, *ADL* indicates that the individual had ADL limitations at time *t+1* but none at time *t*, *CI* indicates the onset ofbetween time *t* and *t+1*, and *AGE* indicates age in years at time *t*. It is impossible for us to allow a different coefficient for all possible health transitions, so instead we focus on decisive changes for the worse, which are likely to trigger a need for care. We also impose the following constraints: $\beta_5 \geq \beta_4 \geq \beta_3$ (those with more ADL limitations are at least as likely to enter care), $\beta_7 \geq \beta_6$ (conditional on having a cognitive impairment, those with 2 or more ADL limitations are at least as likely to enter care as those with 0-1), $\beta_6 \geq \beta_3$ (those with cognitive impairment and 0-1 ADL limitation are at least as likely to enter care as those with no cognitive impairment and 1 limitation), and $\beta_7 \geq \beta_4$ (those with cognitive impairment and at least 2 ADL limitations are at least as likely to enter care as those with no cognitive impairment and 2). The model assumes that onset of impairment may precipitate entry, as governed by β_8 and β_9.[32] We specify the probability of exiting a nursing home similarly, except that we omit the β_8 and β_9 onset terms.[33]

The fourth step is to estimate transition probabilities between assisted living and other care states. We assume that people only exit from assisted living to nursing homes or death, as people typically sell their home to pay for assisted living. We assign transition probabilities into and out of assisted living so that the percentages of individuals in assisted living facilities in five-year age ranges equals that observed in the 2004 NLTCS data, and we restrict transitions into

[31] An alternative would be to assume that the probability of entering nursing home also depends on care status, as might be the case if home health care was a substitute for institutional care.

[32] The onset of disability may provoke immediate entry for some and gradual entry for others.

[33] The estimation has 14 parameters and 14 moments. We weigh the moments to reflect their relative importance for characterizing lifetime patterns of care use. To scale moments to the same units, we express all differences between simulated and sample statistics as percentage deviations from their means. We use a grid search to estimate the betas, but estimating them all simultaneously using a fine grid exceeds the limits of even multi-core computers using parallel processing – the number of calculations equals the number of grid points to the power of the number of betas. We first use a coarse grid; even so, it is not possible to estimate all the betas simultaneously, and we therefore initially constrain β_3-β_7 to take a single value, while allowing the other betas to vary. We use the Matlab fminsearch function to refine our estimates. We then remove the constraint on the values of β_3-β_7 and re-estimate the values of all the betas, again using fminsearch. A danger is that this might arrive at a local rather than a global minimum. We tested our algorithm by simulating data given assumed transition probabilities, calculating sample characteristics, and checking that our computational technique can recover betas that yield the assumed transition probabilities

assisted living to occur with a positive probability only upon the onset of two or more ADLs or cognitive impairment for those who do not enter a nursing home. The fifth step is to assume that all individuals with two or more ADL limitations or who have a cognitive impairment and who are not in assisted living or nursing home care status are eligible for home health care.

The above procedures yield transition probabilities that vary with health states at time t and $t+1$, and with age and gender. Our sixth and final step is to use our Monte-Carlo simulations to calculate unconditional transition probabilities for the use of research that only requires care probabilities that vary with age and gender.[34]

4. Results

The Health Transition Matrix

We begin by showing our parameter estimates for the health transition model in equation (2), which we estimated using maximum likelihood. The parameters for the health transition model indicate how age, sex, and a time trend affect the transition from one state of impairment to another. We bootstrapped the confidence intervals, and almost all the coefficients are statistically significant at the 99% level or better except for the overall likelihood of transitioning from having two ADLs to being deceased (represented by parameter a_{58}) the gender differential for the likelihood of health improvement (represented by the lower half of the b_{ij} matrix) and the time trend for the likelihood of death (represented by the last column of the d_{ij} matrix).[35]

As the coefficients are difficult to interpret in isolation, their estimated values are reported in Appendix Table 5, and we focus here on how well the estimates fit observed values of monthly impairment transitions. The two panels of Table 4 compare the observed and fitted 1999-2004 transition matrices for females aged 75-84 in 1999, with each row summing to 100 percent. Overall, fitted values are close to observed values. To illustrate, 49.7 percent of women who were free of disability in 1999 were also free of disability in 2004. The model predicts a value of 52.1 percent. For those who were well in 1999, the next most likely transition is to state 2, experiencing an inability to perform IADLs (22.6 percent observed, 19.0 predicted) and then

[34] We generate 100,000 Monte Carlo simulations of combined health and care states, a 100,000 by 553 months by 2 (health state and care state) matrix. We calculate the percentages of people aged 65 who were in a care state at month t and in each care state at $t+1$, yielding an unconditional transition matrix for that care state.

[35] For both the health transition and care transition estimation, we drew 1000 bootstrapped samples in order to compute confidence intervals. When the number of observations per cell is relatively small, then the bootstrap may yield a better approximation of the confidence intervals than the analytical approach.

to state 8, death (15.3 percent observed, 16.9 predicted). Meanwhile, among those in state 3 with 1 ADL limitation in 1999, some returned to wellness (14.4 percent observed, 9.9 fitted).

The Care Status Transition Matrices

Table 5 reports the parameters for men and women, respectively, of β_3 to β_{10} obtained from estimating the nursing home care transition model in equation (3). We bootstrapped the confidence intervals, and all the parameter estimates are statistically significant at the 99% level of better. As expected, an increase in the number of ADLs increases the likelihood of nursing home entry and stay (with the coefficients becoming less negative), as does the onset of ADL limitations. Cognitive impairment raises the likelihood of entry and of stay, for a given number of ADL limitations, but the onset of cognitive impairment independent of ADLs has only a small effect on the likelihood. These effects are a little greater for men than for women. Table 6 compares the care characteristics of the HRS sample with those of our simulated individuals, calculated using the above coefficients. The characteristics of the simulated data are quite close to most of the HRS statistics that we match in our estimation. Both the model and the HRS suggest that 44 percent of men and 58 percent of women will use nursing home care. We predict the age at first use to be slightly higher for men and the same for women (age 81 for men versus 80 in the HRS, and 82 versus 82 for women), a relatively high probability of staying in care for more than a year for men (26 percent simulated versus 22 in the HRS) compared to the same probability for women, and a relatively high probability of a having a single lifetime stay in a nursing home (69 percent simulated versus 65 in the HRS for men, 57 versus 55 for women). Our unconditional duration of lifetime nursing home stays is very close (0.38 years simulated versus 0.37 in the HRS for men, 0.83 versus 0.79 for women), while our predicted probability of ever leaving care alive is somewhat overestimated (77 percent simulated versus 62 observed for men in the HRS, 78 simulated versus 66 observed for women).[36]

The model yields a total of 46 unconditional transition matrices, one for each age from 65 to 110, and 2,576 conditional transition matrices, one for each age and each of 56 health status transitions. For example, a man aged 85 receiving home health care has an 85.9 percent chance of continuing to receive home health care in the following month, a 5.1 percent chance of not

[36] In consequence, our model will tend to over-estimate willingness to pay for long-term care insurance and, if anything, underestimate Medicaid crowd-out.

needing care (returning to the "healthy" care state), a 6.4 percent chance of moving to assisted living, a 0.5 percent chance of moving to a nursing home, and a 2.1 percent chance of dying.

5. The Impact on Demand for Long-Term Care Insurance Demand

Our new transition matrices yield several insights about the demand for long-term care insurance. As a result of applying our new matrices, demand for insurance is substantially reduced by three factors: the expected present values of benefit payouts fall and premiums paid rise, reducing the money's worth of observed policies; the risk of extreme care costs falls, reducing the value of observed policies to risk-averse individuals; and Medicare and Medigap insurance cover many initial care spells, which we use our monthly transition model to quantify.

We begin with the first reason why demand for insurance is affected by our new estimates. Demand for a given policy depends on money's worth, defined as the expected present value of benefits (which rises with care use) divided by the expected present value of premiums (which falls with care use because premiums are no longer paid upon using care). We compute money's worth of the typical long-term care policy that Brown and Finkelstein (2007) evaluated. Using premium data from 2002 and the Robinson care transition probabilities, they computed money's worth of 0.50 for men and 1.06 for women, indicating that the typical policy was actuarially unfair for men and slightly better than actuarially fair for women (reflecting unisex pricing and women's greater risk of using care). Using their premium data, but applying our transition probabilities, we compute money's worths at 0.39 and 0.79, respectively. The substantial reduction in money's worth of typical policies reflects two factors. First, the expected present value of premiums paid rises – for example, by 5.5 percent for men because they stay healthy for 18 months longer on average. Second, the expected present value of benefits decreases – by 17 percent for men because of a substantial drop in their home health care costs, arising because of the decline in impairment that we highlighted in Table 3A, offset by a small increase in assisted living costs.[37]

These patterns make policies less valuable for individuals whatever their risk preference. Next, we consider the impact on risk-averse individuals of both the reduction in money's worth

[37] While we showed in Table 3A that impairment declined between 1984 and 2004, we also showed that home health care *use* stayed steady in Table 3B. Further analysis showed that the effect on home health care use of the decline in impairment was offset by an increased propensity to use home health care among the less impaired. Recall that our statistical model of care use focuses on care that would be paid for by Medicaid or private insurance, and the decline in impairment has lowered eligible home health care *costs*.

and the change that we identified earlier in the distribution of care spells, from the lower probability, higher cost events implied by the Robinson transition probabilities to the higher probability, lower cost events implied by ours. To investigate this, we revisit the optimization model of Brown and Finkelstein (2008), who calculate a single individual's willingness to pay for a $100 daily benefit unlimited duration policy at market loads. We recalculate willingness to pay using our new transition probabilities but retaining all the other model parameters.

The model begins with an individual who is retired and in good health at age 65 choosing consumption each period to maximize expected lifetime utility.[38] Each month, individuals face probabilities, varying with age and gender, of transitioning among the five care states described above. The model carefully replicates features of the Medicaid program that affect willingness to pay, assumes a time preference rate of three percent and constant relative risk aversion with a coefficient of three. The model is solved numerically for wealth deciles of single individuals observed in the HRS. Willingness to pay is calculated by first assuming the individual purchases long-term care insurance, calculating the optimal wealth decumulation strategy, and noting expected discounted lifetime utility. Long-term insurance then becomes unavailable and the optimal decumulation strategy is recalculated. Willingness to pay for long-term care insurance equals the amount by which age-65 wealth must be increased so that the individual can achieve the same expected discounted lifetime utility when he does not purchase insurance. If willingness to pay is negative, the individual prefers not to purchase insurance.

Figures 3A and 3B show the amounts single men and women would be willing to pay for long-term care insurance at the 30th to the 90th percentile of the wealth distribution under the base case of the Robinson transition matrices and two counterfactuals using our transition matrices, one excluding and one incorporating Medicare (which we will discuss shortly).[39] In the model that excludes Medicare, single men with the 90th percentile value of wealth would be willing to pay $24,600 for access to the long-term care insurance market, given the Robinson transition probabilities. Under our revised transition probabilities, willingness to pay falls to $-3,700.

[38] People in poor health are unable to obtain private insurance, so they (and we) focus on those who are well. The slightly different definition of health based on ADLs that we use yields a similar percentage of the sample that is well (for example, 87.9% of men, based on our calculation from Robinson, and 90.9% here). Our slightly less select group may be slightly more likely to go into care and to purchase insurance, so if anything this approach understates the impact of using our corrected matrices. We use the same transition matrices to calculate both premiums and willingness to pay, and therefore use the same sales load, in each scenario.

[39] Willingness to pay at the 10th and 20th percentiles is undefined because the amount the individual would pay not to have insurance exceeds total financial wealth.

Women have a higher willingness-to-pay than men because of their higher risk of using care and higher average duration of care. Under the original transition matrix, 36 percent of men and 40 percent of women had a positive willingness to pay for long-term care insurance. Under our revised transition matrix, only 5 percent of men and 21 percent of women had a positive willingness to pay. The consequence of the overall changes in predicted nursing home use is an increase in projected Medicaid participation at all percentiles of the wealth distribution, for example rising from 3.7 to 6.2 percent for men at the 90th percentile of wealth and from 28.2 to 32.5 percent for men at the 50th percentile.[40] At the same time, the decline in the average duration of nursing home stays reduces projected Medicaid costs, compared to projections using the Robinson transition probabilities. The consequence is little change in average Medicaid costs across the wealth distribution.[41]

These and other similar calculations overlook the role of Medicare in paying part of nursing home costs. Medicare acts as the primary payer for the first 100 days of many nursing home stays, as we noted earlier, and should reduce willingness to pay for private insurance. We can use our estimates to compute the share of all nursing home days represented by the first three months of a stay. Among men and women, respectively, 28 and 22 percent of the total days spent in a nursing home in our simulated population comprise stays that fall within the first three months, similar to the 25.2 percent of all long-term care costs covered by Medicare in 2013 but higher than in earlier years. In any case, this represents an upper bound of Medicare-covered stays in nursing homes, since not all stays qualify for Medicare.

We use our upper-bound calculation of Medicare-covered stays to compute an upper-bound prediction of the effect of Medicare on willingness to pay.[42] In Figures 3A and 3B, when Medicare covers the first three months of all care, then no men are willing to pay for private insurance (down from 5 percent above), while 16 percent of women (down from 21 percent)

---

[40] The figures assume that people do not purchase long-term care insurance. If they made optimal purchase decisions about the policy we describe earlier in the text, then the figures for Medicaid participation are 3.9 and 5.5 percent for men at the 90th percentile of wealth under the old and new transition matrices.

[41] Average Medicaid costs are projected to rise for all men and rise for women in the upper two deciles of the wealth distribution, while falling for women in the lower eight deciles. All of these projected changes in average costs due to the new transition probabilities are smaller than $5,000.

[42] Although Medicare co-pays are substantial, they are typically covered by Medigap insurance. The calculations further assume that insurers disregard Medicare-covered care when determining elimination periods so that individuals would not choose to substitute a less expensive 90-day elimination period policy for a zero day elimination period policy.

have a positive willingness to pay. This arises because insurance premiums do not change while the whole distribution of long-term care costs falls.

In sum, this analysis substantially strengthens the conclusion emphasized by Brown and Finkelstein that public insurance crowds out much of the private long-term care insurance market. As a result, applying our new care transition probabilities reduces the possible relevance of behavioral explanations of low private insurance coverage.

6. Conclusion

We demonstrate two important features of the risk of requiring long-term care use. We show that physical impairment and most use of care have declined since the early 1980s. We also show that the commonly used Robinson (2002) model of long-term care expectations, while capturing the recent unconditional mean duration of nursing home stays, has design features that result in an overestimate of the conditional mean duration of nursing home stays among those entering care and a corresponding underestimate of the risk of ever requiring nursing home care, even compared to recent lower rates of care use. We modify and update the Robinson model using recent data from both the NLTCS and the HRS and provide new transition probabilities among health impairment states and among types of care. These transition matrices vary with age and gender and are available from the authors on request.

The new transition probabilities substantially reduce the value of long-term care insurance for single individuals in the presence of both Medicaid and Medicare. Brown and Finkelstein (2008) already found substantial crowd-out from Medicaid using the Robinson (2002) estimates of care needs. They found that the richest 36 percent of single men and 40 percent of single women should have a positive willingness to pay for long term care insurance at market loads in the presence of Medicaid. These wealth thresholds jump substantially when we use our new transition probabilities, leaving only the richest 5 percent of men and 21 percent of women willing to pay for any coverage. Furthermore, our new estimates give a straightforward upper bound on crowd-out from Medicare coverage of the first 100 days of many nursing home stays; the wealth thresholds if Medicare covered all such stays fall to zero for single men and 16 percent for single women. These values of optimal long-term care insurance holding, whether considering Medicare or not, are much closer to the 9 percent coverage rate that we observe in the HRS among single individuals aged 65 or older.[43]

Friedberg, Hou, Sun, and Webb (2015) undertake similar calculations for married couples and find lower valuations of long-term care at each comparable wealth level (that is, adjusted by consumption equivalence scales) for married couples than for singles. In sum, our research helps to resolve the puzzle of low private long-term care insurance coverage, with crowd-out from social insurance providing an even stronger explanation for the low level of coverage than previously thought.

[43] This statistic is lower than is calculated in early waves of the HRS. New questions that were asked as of 2002 allow us to treat as not having insurance HRS participants who state that they have long-term care insurance but later state that the policy in question is in fact one of the health insurance policies covered earlier in the interview.

References

Ameriks, John, Andrew Caplin, Steven Laufer, and Stijn Van Nieuwerburgh. 2011. "The Joy of Giving or Assisted Living? Using Strategic Surveys to Separate Public Care Aversion from Bequest Motives." *Journal of Finance* 55(2): 519-561.

Arling, Greg, Shelley Hagan, and Harald Buhaug. "The Feasibility of a Public-Private Long-Term Care Financing Plan." *Medical Care* 1992(30): 699.

Brown, Jeffrey R., and Amy Finkelstein. 2004. "The Interaction of Public and Private Insurance: Medicaid and the Long-Term Care Insurance Market." Working Paper 10989. Cambridge, MA: National Bureau of Economic Research.

Brown, Jeffrey R., Norma B. Coe, and Amy Finkelstein. 2007. "Medicaid Crowd-Out of Private Long-Term Care Insurance: Evidence from the Health and Retirement Survey." In Tax Policy and the Economy, ed. James M. Poterba, 1–34. Cambridge, MA: MIT Press.

Brown, Jeffrey R., and Amy Finkelstein. 2008. "The Interaction of Public and Private Insurance: Medicaid and the Long-Term Care Insurance Market." *American Economic Review* 98(3): 1083-1102.

Byrne, David, Michelle Goeree, Bridget Hiedemann, and Steven Stern. 2009. "Formal Home Health Care, Informal Care, and Family Decision-Making." *International Economic Review* 50(4): 1205-1242.

Cohen, Marc A., Jocelyn Gordon, and Jessica Miller. 2011. "Understanding How Long-Term Care Benefit Triggers Are Implemented in the Private Insurance Setting." CLASS Technical Assistance Brief Series 3. Long Beach, CA: The SCAN Foundation.

Cohen, Marc A., Eileen J. Tell., and Stanley S. Wallack. 1986. "The Lifetime Risks and Costs of Nursing Home Use Among the Elderly." *Medical Care* 41(6): 785-792.

Centers for Medicare and Medicaid Services. 2013. "National Health Expenditure Projections 2012-2022." Available at: http://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/downloads/proj2012.pdf.

Costa-Font, Joan, and Christophe Courbage. 2014. "Crowding Out of Long-Term Care Insurance: Evidence from European Expectations Data." Working Paper 4910. München, Germany: CESifo.

Dick, Andrew, Alan M. Garber, and Thomas E. MaCurdy. 1994. "Forecasting Nursing Home Utilization of Elderly Americans." in *Studies in the Economics of Aging.* Chicago, IL: University of Chicago Press: 365-394.

Fong, Joelle H., Adam W. Shao, and Michael Sherris. 2013. "Multi-State Actuarial Models of Functional Disability." Research Paper 2013ACTL14. Sydney, Australia: Australian School of Business.

Friedberg, Leora, Wei Sun, and Anthony Webb. 2015. "Medicaid and Crowd-out of Long-Term Care Insurance." Working paper.

Gustman, Alan, and Thomas Steinmeier. 2005. "The Social Security Early Entitlement Age in a Structural Model of Retirement and Wealth." *Journal of Public Economics* 89 (2-3): 441-463.

Hiedemann, Bridget, Michelle Sovinsky, and Steven Stern. 2013. "Will You Still Want Me Tomorrow? The Dynamics of Families' Long-Term Care Arrangements." Manuscript. University of Virginia.

Hurd, Michael, Pierre-Carl Michaud, and Susann Rohwedder. 2014. "The Lifetime Risk of Nursing Home Use." In *Discoveries in the Economics of Aging* edited by David A. Wise, 81-109. Chicago, IL: University of Chicago Press.

Kelly, Anne, Jessamyn Conell-Price, Kenneth Covinsky, Irena Stijacic Cenzer, Anna Chang, W. John Boscardin, and Alexaner K. Smith. 2010. "Length of Stay for Older Adults Residing in Nursing Homes at the End of Life." *Journal of the American Geriatrics Society* 58(9): 1701-1706.

Kemper, Peter, and Christopher M. Murtaugh. 1991. "Lifetime Use of Nursing Home Care." *New England Journal of Medicine* 324: 595-600.

Liang, Jersey, Xian Liu, Edward Tu, and Nancy Whitelaw. 1996. "Probabilities and Lifetime Durations of Short-Stay Hospital and Nursing Home Use in the United States, 1985." *Medical Care* 34(10): 1018-1036.

Manton, Kenneth G., and Xiliang Gu. 2001. "Changes in the Prevalence of Chronic Disability in the United States Black and Non-Black Population Above 65 from 1982 to 1999." *Proceedings of the National Academy of Sciences of the United States of America* 98: 6354-59.

Manton, Kenneth G., Xiliang Gu, and Vicki L. Lamb. 2006. "Change in Chronic Disability from 1982 to 2004/2005 as Measured by Long-Term Changes in Function and Health in the U.S. Elderly Population." *Proceedings of the National Academy of Sciences of the United States of America* 103(48): 18374-79.

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

Reichling, Felix and Kent Smetters. 2013. "Optimal Annuitization with Stochastic Mortality Probabilities." Working Paper 2013-05. Washington, DC: Congressional Budget Office.

Robinson, James. 2002. "A Long-Term Care Status Transition Model." Working paper, University of Wisconsin.

Rubin, Donald. 1987. *Multiple Imputation for Nonresponse in Surveys*. New York, NY: J. Wiley & Sons.

Spillman, Brenda C. and James Lubitz. 2002. "New Estimates of Lifetime Nursing Home Use: Have Patterns of Use Changed?" *Medical Care* 40(10): 965-975.

Stallard, Eric. 2011. "Estimates of the Incidence, Prevalence, Duration, Intensity, and Cost of Chronic Disability among the U.S. Elderly." *North American Actuarial Journal* 15(1): 32-58.

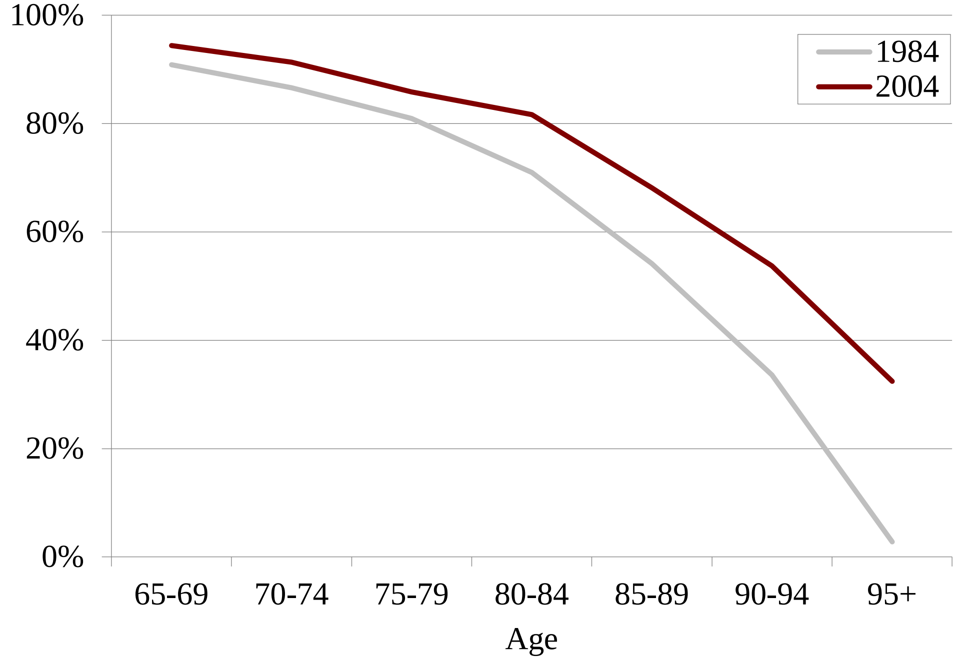
Stallard, Eric and Robert K.W. Yee. 1999. "Non-Insured Home and Community-Based Long-Term Care Incidence and Continuance Tables." Schaumburg, IL: Society of Actuaries Long-Term Care Experience Committee.

Sun, Wei and Anthony Webb. 2013. "Can Long-Term Care Insurance Partnership Programs Increase Coverage and Reduce Medicaid Costs?" Working Paper 2013-8. Chestnut Hill, MA: Center for Retirement Research at Boston College.

U.S. Department of Health and Human Services. 2009. "The National Nursing Home Survey: 2004 Overview." Vital and Health Statistics Series 13, No.167. Hyattsville, MD: Centers for Disease Control and Prevention.

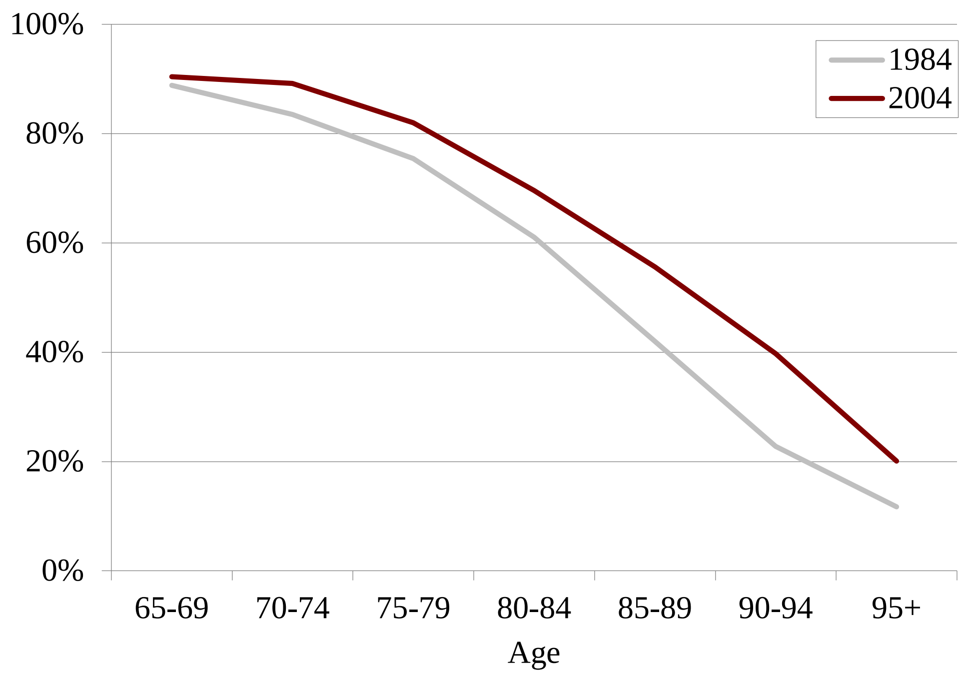
U.S. Department of Health and Human Services. 2015. "Receiving Long-Term Care Insurance Benefits" http://longtermcare.gov/costs-how-to-pay/what-is-long-term-care-insurance/when-your-coverage-begins/

Figure 1A. *Share of Men Who Are Well, By Age*



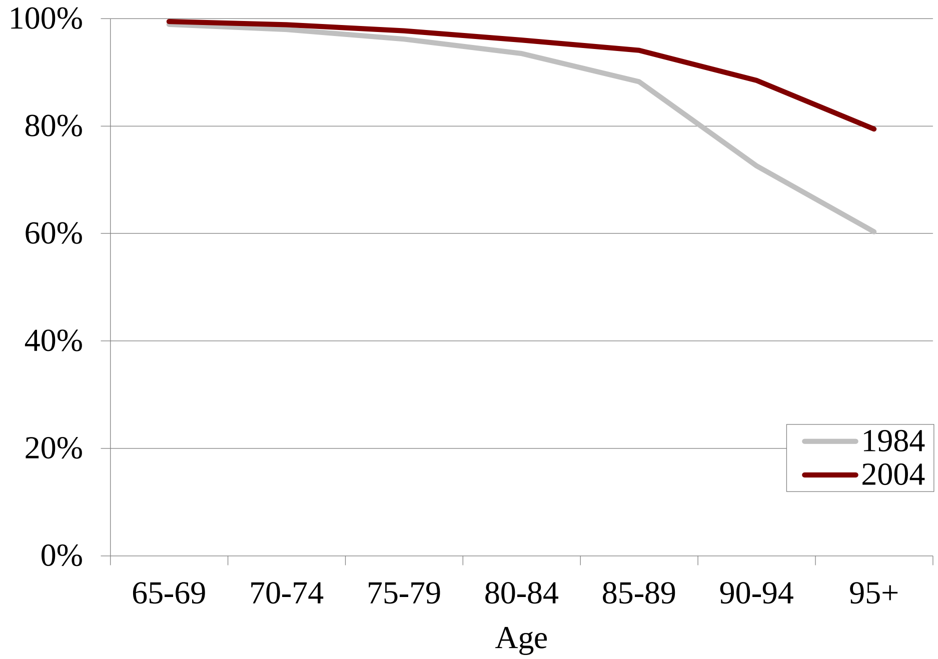
Source: NLTCS 1984, 2004.

Figure 1B. *Share of Women Who Are Well, by Age*



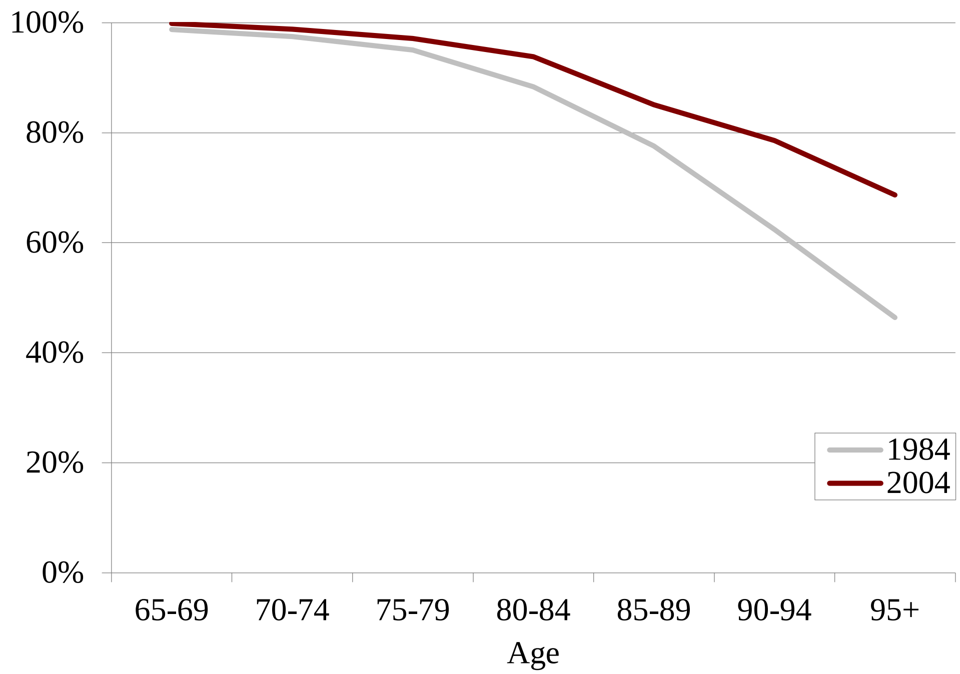
Source: NLTCS 1984, 2004.

Figure 2A. *Share of Men Who Live Outside of a Nursing Home, by Age*



Source: NLTCS 1984, 2004.

Figure 2B. *Share of Women Who Live Outside of a Nursing Home, by Age*



Source: NLTCS 1984, 2004.

Figure 3A. *Willingness to Pay for Private LTCI ($100 Daily Benefit Cap, Market Load) – Men*

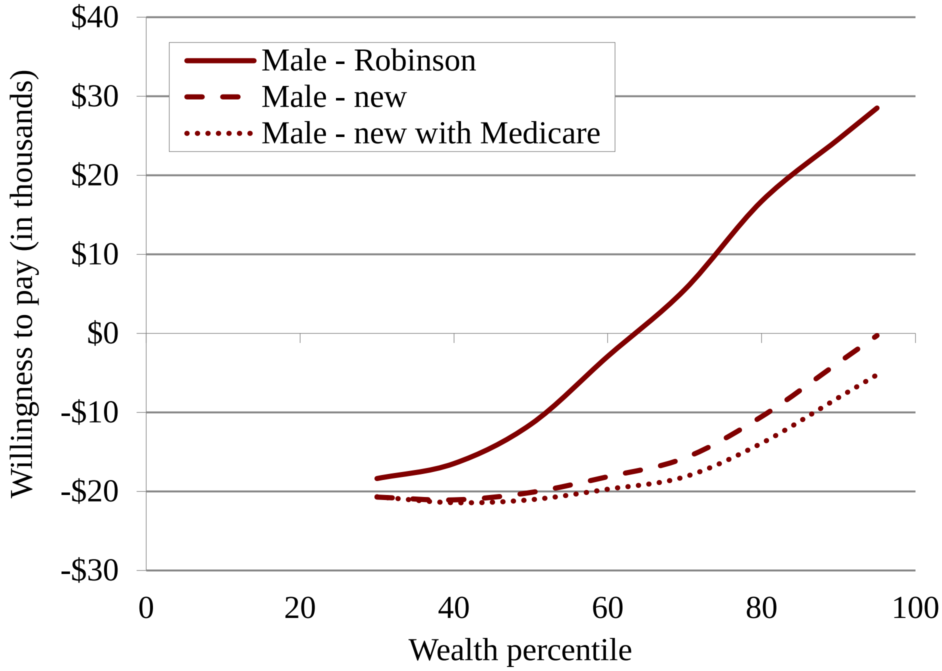
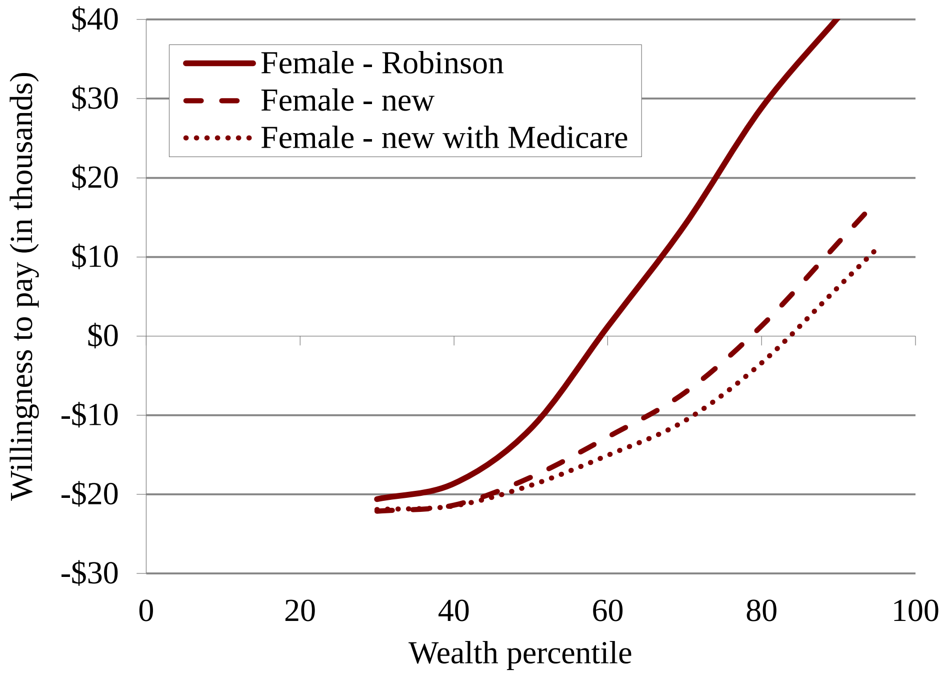


Figure 3B. *Willingness to Pay for Private LTCI ($100 Daily Benefit Cap, Market Load) – Women*



Notes: Comparison using Robinson care use transition matrices, new transition matrices, and new transition matrices with Medicare payments for care.

Table 1. *Previous Estimates of Long-Term Care Utilization*

	Arling, Hagan, and Buhang	Kemper and Murtaugh	Cohen, Tell, and Wallack	Dick, Garber, and MaCurdy	Kelly et.al.	Liang, Liu,Tu, and Whitelaw	Spillman and Lubitz	Hurd, Michaud, and Rohwedder	Robinson
Dataset used	Wisconsin LTC Use and Cost Model	1986 Mortality Followback Survey	1977 Current Medicare Survey	NLTCS, NNHS	HRS (7 waves of AHEAD data)	1985 NNHS, 1985 NHDS,1987 National Medical Care Expenditure Survey	National Mortality Followback Survey	HRS, Waves 1-10	NLTCS
Period covered	1987-1989	Pre 1986	1977-1978	1982-1984	1992-2006	1985	1986, 1993, and 2000 (projected)	1992-2010	1982-1989
Uses exit data	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
Estimate of probability of using care after age 65:									
Males	55%	33%	31%	36%	Not reported	Not reported	33%	50%	27%
Females		52%	52%	35%			47%	65%	44%
Unconditional mean duration of care in years									
Males	1.12	Not reported	Not reported	0.48	Not reported	2.28	1.1	0.38	0.35
Females				0.73				0.78	0.88
Conditional mean duration in years									
Males	2.04	Not reported	Not reported	1.34	0.86	Not reported	2.5	0.76	1.30
Females				2.09	1.33			1.20	2.00

-cont'd-

Table 1. *Previous Estimates of Long-Term Care Utilization* (cont'd)

	Arling, Hagan, and Buhang	Kemper and Murtaugh	Cohen, Tell, and Wallack	Dick, Garber, and MaCurdy	Kelly et.al.	Liang, Liu,Tu, and Whitelaw	Spillman and Lubitz	Hurd, Michaud, and Rohwedder	Robinson
Other results		Project 14% of men and 31% women aged 65 in 1990 will spend more than a year in nursing home	25% chance of spending more than a year, conditional on entry						
Research methodology	Simulations based on Wisconsin LTC Use and Cost Model	Retrospective study based on interviews with next of kin	Nursing home entry inferred from data on whether the respondent had been visited by a physician in a nursing home.	Simulations based on 1982-84 NLTCS data	Sample limited to individuals who died in a nursing home	Construct multi state life table based on age-specific transition probabilities	Retrospective study based on interviews with next of kin.	Analysis of HRS panel data	Uses NLTCS to estimate health status transition probabilities. Assigns care status conditional on health status

Notes: HRS = Health and Retirement Study. NLTCS = National Long-Term Care Survey. NNHS = National Nursing Home Survey. AHEAD = Asset and Health Dynamics among the oldest old. NHDS = National Hospital Discharge Survey. Kemper and Murtaugh estimates are for birth cohort turning 65 in 1990. Hurd, Michaud, and Rohwedder calculate utilization from age 50.

Table 2. *Comparison of Selected Robinson, HRS Statistics on Nursing Home Use*

	Men		Women	
	Robinson	HRS	Robinson	HRS
Probability of ever using a nursing home	0.27	0.44	0.44	0.58
Average age of first use, conditional on use	83	80	84	82
Mean years in care:				
Unconditional	0.35	0.37	0.88	0.79
Conditional on ever using	1.30	0.85	2.00	1.37
Probability of using a nursing home for:				
1 year	0.33	0.22	0.42	0.38
3 years	0.12	0.08	0.22	0.16
5 years	0.05	0.02	0.12	0.07
Conditional probability of ever exiting alive	0.65	0.62	0.66	0.66
Conditional probability of only one stay	0.75	0.65	0.65	0.55

Sources: Robinson data is as reported in Table 1 of Brown and Finkelstein (2008); and authors' calculations.

Table 3A. *Comparison of Health Status 1984 and 2004 NLTCS*

Age	65-69	70-74	75-79	80-84	85-89	90-94	95+	All 65+
NLTCS wave				1984				
Men								
Well	90.9%	86.6%	81.0%	71.0%	54.2%	33.6%	2.8%	80.8%
Unable to perform IADL but no ADLs	5.4	7.5	10.9	15.0	20.9	22.1	28.9	10.0
No cognitive impairment and:								
Unable to perform 1 ADL	1.1	1.5	1.3	3.0	5.0	9.2	20.7	2.0
Unable to perform 2ADLs	0.5	0.6	0.8	0.9	2.6	5.6	8.4	0.9
Unable to perform 3+ ADLs	1.1	1.5	2.7	4.0	8.2	11.1	16.0	2.7
Cognitive impairment and:								
Unable to perform < 2 ADLs	0.5	1.5	1.6	2.6	5.5	6.3	7.2	1.8
Unable to perform 2+ ADLs	0.5	0.8	1.7	3.5	3.6	12.1	16.0	1.8
Women								
Well	88.8%	83.5%	75.4%	61.0%	42.0%	22.8%	11.7%	71.0%
Unable to perform IADL	7.2	10.3	13.2	17.6	19.8	17.8	15.9	12.8
No cognitive impairment and:								
Unable to perform 1 ADL	1.4	2.4	3.1	5.7	7.9	10.8	12.8	4.0
Unable to perform 2ADLs	0.6	0.5	1.0	1.3	2.0	3.1	7.7	1.1
Unable to perform 3+ ADLs	1.0	1.6	3.2	6.0	11.0	20.6	28.5	4.8
Cognitive impairment and:								
Unable to perform < 2 ADLs	0.5	1.0	2.6	4.2	8.8	9.1	6.8	3.1
Unable to perform 2+ ADLs	0.5	0.7	1.5	4.2	8.5	15.8	16.6	3.2

-cont'd-

Table 3A. *Comparison of Health Status 1984 and 2004 NLTCS* (cont'd)

Age	65-69	70-74	75-79	80-84	85-89	90-94	95+	All 65+
NLTCS wave				2004				
Men								
Well	94.4%	91.3%	85.9%	81.7%	68.2%	53.7%	32.4%	86.3%
Unable to perform I ADL	3.5	4.2	5.1	7.2	14.2	19.3	30.8	6.0
No cognitive impairment and:								
Unable to perform 1 ADL	1.0	1.8	3.7	4.2	6.2	5.6	6.8	2.8
Unable to perform 2ADLs	0.2	0.1	1.2	1.5	1.7	7.1	2.6	0.9
Unable to perform 3+ ADLs	0.6	1.4	2.4	3.2	5.1	7.1	19.5	2.2
Cognitive impairment and:								
Unable to perform < 2 ADLs	0.2	0.7	1.1	1.1	3.5	3.4	5.2	1.0
Unable to perform 2+ ADLs	0.1	0.5	0.7	1.2	1.1	3.8	2.7	0.7
Women								
Well	90.4%	89.2%	82.0%	69.6%	55.6%	39.7%	20.1%	77.3%
Unable to perform I ADL	4.4	4.6	7.6	11.8	14.3	18.9	15.8	8.4
No cognitive impairment and:								
Unable to perform 1 ADL	3.3	3.6	4.9	8.0	9.9	11.4	10.7	5.8
Unable to perform 2ADLs	0.7	0.8	1.4	1.5	3.0	4.6	4.5	1.5
Unable to perform 3+ ADLs	0.8	1.4	2.4	5.0	11.3	15.1	32.0	4.4
Cognitive impairment and:								
Unable to perform < 2 ADLs	0.3	0.1	0.8	1.7	2.5	4.2	5.6	1.1
Unable to perform 2+ ADLs	0.2	0.2	1.0	2.3	3.3	6.2	11.4	1.5

Note: PNAS weights.
Source: Authors' calculations.

Table 3B. *Comparison of Care Status 1984 and 2004 NLTCS*

Age	65-69	70-74	75-79	80-84	85-89	90-94	95+	all 65+
NLTCS Wave				1984				
Men								
Receiving home health care	0.4%	0.8%	1.0%	2.3%	2.8%	7.8%	11.8%	1.3%
In assisted living	0.7	1.1	1.4	2.1	3.4	1.6	6.3	1.4
In nursing home	1.1	2.0	3.8	6.5	11.8	27.4	39.7	4.1
Women								
Receiving home health care	0.5%	0.8%	1.5%	2.1%	3.7%	5.7%	3.1%	1.7%
In assisted living	1.2	1.8	3.3	4.4	4.7	5.3	5.2	2.9
In nursing home	1.3	2.5	4.9	11.7	22.4	37.6	53.6	8.8
NLTCS Wave				2004				
Men								
Receiving home health care	0.5%	0.9%	1.2%	1.5%	2.1%	5.1%	4.3%	1.2%
In assisted living	0.1	0.4	0.6	1.6	3.1	3.1	8.1	0.9
In nursing home	0.5	1.1	2.3	4.0	5.9	11.5	20.6	2.4
Women								
Receiving home health care	1.0%	0.9%	1.3%	2.3%	3.2%	4.4%	7.4%	1.8%
In assisted living	0.4	0.3	0.9	2.2	4.8	7.2	14.0	1.8
In nursing home	0.2	1.2	2.9	6.2	14.9	21.4	31.3	5.2

Note: PNAS weights.
Source: Authors' calculations.

Table 4. *Observed and Fitted Health Status Transition Matrices Females 75-84, 1999-2004*

1999 health status	Count	2004 health status: 1 Well	2 IALD only	3 1 ADL	4 2 ADLs	5 3+ ADLs	6 Less than 2 ADLs + CI	7 2+ ADLs + CI	8 Deceased
1. Well	3,587	49.7 %	22.6 %	5.2 %	1.1 %	3.0 %	1.6 %	1.6 %	15.3 %
2. IADL only	731	3.9	34.2	7.9	2.1	7.2	1.1	2.8	40.8
3. 1 ADL	188	14.4	24.5	11.7	6.7	6.2	3.5	1.0	32.0
4. 2 ADLs	48	1.3	19.5	2.9	0.0	14.0	0.0	0.0	62.2
5. 3+ ADLs	140	1.0	5.7	0.0	1.8	13.1	0.9	0.0	77.4
6. Less than 2 ADLs + CI	16	1.7	19.9	8.0	1.2	11.7	1.2	6.0	50.3
7. 2+ ADLs + CI	22	0.0	6.1	0.0	3.8	11.2	0.0	2.3	76.6
					Fitted values				
1. Well		52.1 %	19.0 %	3.6 %	1.1 %	3.5 %	2.0 %	1.8 %	16.9 %
2. IADL only		10.7	35.3	7.2	2.3	5.3	3.5	3.0	32.7
3. 1 ADL		9.9	30.0	6.5	2.2	6.0	3.2	3.3	38.9
4. 2 ADLs		5.6	21.3	5.1	2.3	8.3	2.3	4.2	51.0
5. 3+ ADLs		2.2	10.9	2.8	1.7	7.9	1.2	3.9	69.3
6. Less than 2 ADLs + CI		5.6	24.2	5.9	2.4	8.7	4.2	4.7	44.3
7. 2+ ADLs + CI		2.0	11.2	3.0	1.9	9.5	1.2	4.7	66.3

Source: Authors' calculations.

Table 5. *Coefficient Estimates for Nursing Home Entry and Stay*

	Male	Entry	Stay
β_3	1 ADLs	-6.535	-7.261
β_4	2 ADLs	-6.442	-5.916
β_5	3+ ADLs	-6.163	-4.380
β_6	Less than 2 ADLs + CI	-6.079	-5.607
β_7	2+ ADLs + CI	-5.877	-3.269
β_8	First has ADL	6.218	-
β_9	First has CI	0.514	-
β_{10}	Age	0.058	0.411

Source: Authors' calculations.

	Female	Entry	Stay
β_3	1 ADLs	-6.302	-7.801
β_4	2 ADLs	-5.271	-5.509
β_5	3+ ADLs	-3.399	-5.232
β_6	Less than 2 ADLs + CI	-5.138	-6.826
β_7	2+ ADLs + CI	-5.036	-3.347
β_8	First has ADL	5.500	-
β_9	First has CI	0.509	-
β_{10}	Age	0.017	0.420

Source: Authors' estimates by method of simulated moments. Bootstrapped confidence intervals indicate that all coefficients are statistically significant at the 99% confidence level or better. See text for further details.

Table 6. *Comparison of HRS Sample, Simulated Moments on Nursing Home Use*

	Men		Women	
	HRS	Simulated	HRS	Simulated
Probability of ever using nursing home care	0.44	0.44	0.58	0.58
Average age of first use, conditional on use	80	81	82	82
Conditional average number of years spent in care	0.85	0.88	1.37	1.39
Conditional probability of using a nursing home for more than:				
1 year	0.22	0.26	0.38	0.38
2 years	0.15	0.13	0.25	0.23
3 years	0.08	0.07	0.16	0.14
4 years	0.05	0.04	0.11	0.09
5 years	0.02	0.02	0.07	0.06
6 years	0.02	0.01	0.04	0.04
7 years	0.01	0.00	0.02	0.02
Conditional probability of returning to the community	0.62	0.77	0.66	0.78
Conditional probability of only:				
1 stay	0.65	0.69	0.55	0.57
2 stays	0.21	0.21	0.25	0.26
3 stays	0.07	0.07	0.12	0.11

Source: Authors' calculations.

Appendix

Data: NLTCS sample details

The NLTCS takes steps to maintain a representative sample and also obtain information about the deceased. At each wave, a screener questionnaire is used to divide the sample into the non-disabled, the disabled who live in the community, and the disabled who live in an institution. Those who are non-disabled are asked no further questions in that wave. Those who are disabled and live in the community are administered a community survey. In the first wave, no further questions are asked of those who are institutionalized, but in subsequent waves, they are administered a survey for institutionalized individuals.

The 1982 survey began with 20,485 individuals. About 5000 people die between waves and are replaced by a sample of about that size who attained age 65 subsequent to the previous wave. Between 1982-84, about 3200 died and then 4900 joined the survey in 1984. Between 1984-89, about 6200 died and then 4900 joined the survey in 1989. Between 1989-94, about 5700 died and then 5000 joined in 1994. Not all the prior non-disabled are interviewed in the following wave, and the sampling fraction of prior non-disabled is adjusted to oversample those who are aged over 75. In 1984, the NLTCS interviewed the relatives of participants who had died between 1982 and 1984, and subsequent to 1999, the NLTCS also interviewed the relatives of a subsample of 544 individuals drawn from participants who were alive in 1999, but died between 1999 and 2001.

Data: Definition of assisted living for the care transition model

The NLTCS questions on housing status have changed over time. In 2004, the screener questionnaire asks individuals whether they are living in 1) regular housing, 2) an ALC, CCRC, or Congregate Care Facility (CCF), 3) a nursing wing of a CCRC, or 4) a unit in a nursing, convalescent or rest home, or home for the aged. We follow the NLTCS protocol and categorize all residents of CCRCs as living in assisted living facilities, regardless of whether they are receiving nursing care. In 1999 and previous waves, the survey first identifies whether individuals are living in a nursing home, and then asks the non-institutionalized, "…if this place is part of a building or community intended for older or retired, or disabled persons?" It is not therefore possible to distinguish between ILCs, ALRs, CCRCs and CCFs. For 1999 and previous wave, we follow Robinson (1996) and categorize all accommodation intended for older persons as assisted living facilities. This will likely bias upwards estimates of the utilization of assisted living facilities.[44]

Data: How similar are the NLTCS and HRS?

One of our goals is to use updated data on care needs, and with two possible data sources, we can compare care outcomes at the same date. Excluding the HRS exit interviews in order to assess comparability, the utilization of nursing homes and assisted living facilities in the 2004 HRS is very similar to that in the 2004 NLTCS, which increases our confidence when we combine information from both in order to update the Robinson model.[45] In the HRS 2.4 percent of men and 4.9 percent of women were living in a nursing home at the time of the interview, compared with 2.4 and 5.2 percent of NLTCS participants. It is not possible to make a comparison of the number of separate episodes of institutionalization because of differences in the structure of the questions.[46] We use nursing home data from the HRS because it offers better information about duration of care and because it obtains better information about exit interviews, but the similar rate of care in both recent surveys when excluding the exit interview information is reassuring. It is also not possible to make a similar comparison of rates of home health care utilization because the HRS asks about any care utilization in the last two years whereas the NLTCS asks about care utilization in the last month, so the rate of home health care

[44]Assisted living options include the Independent Living Community (ILC), Assisted living Residence (ALR), and Continuing Care Retirement Community (CCRC). Coe and Boyle (2012) explain their distinguishing features. The NLTCS asks questions that enable us to directly identify residents of ALRs and CCRCs. For purposes of comparison, we also compile information from the HRS. The HRS first asks participants whether they are living in a nursing home. If they are not, the financial respondent answers the housing questionnaire. This does not directly ask about the category of facility used, and the category must be inferred from responses to questions about care services offered. These enable us to determine whether participants are living in an ILC, which does not offer nursing care, as distinct from an ALR or a CCRC. We classify as assisted living an accommodation that has the characteristics of either an ALR or a CCRC, which offer assistance with performing ADLs.

[45] HRS analyses, similar to Tables 3A and B, but excluding exit interviews, are available from the authors on request. The percentages living in a nursing home that we obtain are virtually identical to those reported in Hurd, Michaud, and Rohwedder (2013). In their Table 2 2.4 percent of participants were living in a nursing home at the time of interview. Our sample sizes differ slightly, possibly reflecting differences in the application of sample weights.

[46] The NLTCS comprises three surveys – of institutionalized individuals, of disabled individuals living in the community, and an interview designed to screen out the non-disabled. Institutionalized individuals are asked how many times they were admitted to a nursing home in the last four years and the dates of the last four admissions. Disabled and non-disabled non-institutionalized individuals are asked how many times they have ever been a patient in a nursing home, and the dates and durations of the last two admissions. In 1999, the relatives of some deceased individuals are asked whether they died in a nursing home, and if so, when they were admitted and how long they stayed in the nursing home. They are also asked about the dates and durations of prior institutionalizations. The lack of data on the durations of periods of institutionalization of individuals who were institutionalized in 1999 means that it is not possible to calculate the number of nights stay over any period.

utilization is higher in the HRS but is recorded at too low a frequency to be useful for our analysis.

Model: Definition of health for the health transition model

The NLTCS asks detailed questions about cognitive and physical impairment. Robinson categorizes an individual as suffering from a cognitive impairment if he is unable to provide correct answers to five or more out of a total of ten questions that are designed to measure cognitive functioning. Physical impairment is measured by ADL and IADL limitations. The ADLs comprise eating, bathing, dressing, toileting, being able to get out of bed, and bowel and bladder management. Defining disability involves determining thresholds for disability as a function of limitations that people report, and also deciding how to assign disability rates to those who are screened out in later sub-sampling after providing particular answers about ADLs.

Previous authors have taken various approaches, which we compare in detail in this Appendix and which yield differing trends in disability. For example, we show that Robinson's definitions result in both a high and increasing number of individuals experiencing limitations with IADLs, which seems unrealistic, while other definitions result in substantial declines in ADLs over time. In estimating the health transition matrix, we will include time trends that are allowed to differ for some broad categories of health transitions to account for changes in impairment over time. Besides that, the other major adjustment we make to Robinson's approach is to broaden the definition of disability so that more people are classified as experiencing limitations with ADLs, in agreement with other authors, and fewer with IADLs; we still use a narrower definition than some other authors because our goal is to model disability that triggers long-term care insurance benefits.

Stallard and Yee (1999) and Stallard (2011) presents a seven-tier ordering of limitation for each ADL, ranging from being able to perform the ADL independently, through using special equipment, standby and active help, to being unable to perform the ADL. They also give users of their classification system (insurers or researchers, for example) the option to impose a requirement that individuals require assistance all or most of the time, as opposed to occasionally or some of the time. In contrast, Robinson and Manton, Gu, and Lamb (2006) simply classify individuals as disabled or non-disabled, each relying on slightly different questions.

As shown in Appendix Table 1A, Manton, Gu, and Lamb report substantial declines in ADL limitations and institutionalization rates over the period 1982-2004 using the NLTCS, which we will account for by including a time trend. In contrast, when we apply the Robinson ADL definitions but retain the Manton, Gu, and Lamb sample weights, we find much smaller percentages with multiple ADL limitations and much larger percentages with IADL limitations (Appendix Table 1B). Appendix Tables 2A and 2B cross-tabulate ADL counts based on the two definitions. In both years, a substantial number of individuals lie in the upper right triangle, having more ADLs under the Manton, Gu, and Lamb than the Robinson definition.

To delve further, in Appendix Table 3 we compare the coding of the eating ADL of individuals resident in the community that was adopted by the authors of the above papers with the categorization adopted by Stallard and Yee (1999).[47] The difference in the incidence of the eating ADL limitation between Robinson and Manton, Gu, and Lamb reflects the omission by Robinson of the following types of individuals from the definition of those who are impaired: 1) those who are unable to perform the activity, 2) those who are unable to perform the activity only some of the time or occasionally, 3) those for whom the Robinson definition of disability is stricter because Robinson requires that individuals get help with feeding, cutting meat, or buttering bread, and 4) those identified in follow-up questions as needing stand-by help.[48] The coding of other ADL limitations follows a similar pattern.

With regard to ADLs, our evaluation is that the Manton, Gu, and Lamb classification provides a clearer overall distinction between the disabled and the disability-free because it includes those who merely need special equipment and those who need care part of the time. But, it is perhaps less well suited for our purposes because some of those classified as disabled, for example those only requiring special equipment or stand-by assistance, would be unlikely to qualify for long-term care insurance benefits (Cohen, Gordon, and Miller, 2011). However, the exclusion by Robinson of those unable to perform the activity seems incorrect. We therefore adopt the Robinson classification, except we reclassify those unable to perform the activity as disabled.

[47] Jim Robinson notified us of his coding in correspondence. The Manton, Gu, and Lamb (2006) coding is reported on the NLTCS website.
[48] To illustrate, an individual who reported that they did not need help eating but who reported using special utensils or dishes would be classified by Manton, Gu, and Lamb (2006) as disabled but would be classified by Robinson (1996) as disability-free. An individual who reported that he needed help eating but who reported that he fed himself and did not receive help cutting meat or buttering bread would likewise be classified as disabled by Manton, Gu, and Lamb (2006), but not by Robinson (1996). A table setting out the impact of the above differences in classification on the incidence of each ADL is available on request.

With regard to other limitations, Manton, Gu and Lamb classify people as having an IADL limitation if they report a limitation that is "significant". [49] Robinson classifies people as having an IADL limitation if they report any limitation at all. The Robinson approach yields an implausibly large and increasing percentage of the population as subject to an IADL limitation. We therefore adopt the Manton, Gu and Lamb classification of IADL limitations.

After settling on a definition of IADL and ADL limitations, we follow Robinson in defining states of progressively greater impairment: well (no cognitive impairment and able to perform all ADLs and IADLs, unable to perform 1+ IADL but able to perform ADLs; no cognitive impairment but unable to perform 1, 2, or 3+ ADLs; or cognitive impairment and unable to perform <2 or 2+ ADLs. Table 3A reports the percentages of NLTCS participants in each of these seven impairment states, by age group, in 1984 and 2004, using our preferred definitions. Consistent with previous research, age-specific disability rates declined over the above period. For example, the share of the sample who are well (no IADLs or ADLs) is 54.2% for men aged 85-89 in 1984 and 65.4% in 2004.

Model: The Robinson care status transition model

In modeling nursing home use, Robinson estimates a logistic model based on data from 1984 and 1989. Age is classified as 65-74, 75-84, and 85 plus, and health status takes the six possible values above, along with well and deceased. So, the data yield a total of 72 observations of nursing home utilization by age, gender, impairment state, and year. He includes a dummy for the observation being drawn from 1984 or 1989, so as to account in part for changes over time. He then assigns nursing home status to each simulated individual each month, given age, gender, and health status. Robinson draws a number from the uniform [0,1] distribution for each simulated individual, which serves as their permanent threshold. As long as this threshold exceeds the propensity computed for the individual's sex, attained age, and health status in the NLTCS, and a duration adjustment factor the individual is deemed to remain in the community. Once the individual's nursing home propensity increases to a level above his/her threshold (due to aging or worsening of health), the simulated individual is deemed to be

[49] IADLs include being able to prepare meals, do laundry, shop for groceries, take medicines, or make phone calls without help, manage money, and do light housework.

institutionalized. If the individual's health status improves their prevalence rate may fall below the threshold, resulting in a simulated nursing home discharge to the community.[50]

To illustrate, suppose an individual transitions from being disability-free to having one ADL, remains in that state for many months, and then dies. The probability of nursing home admission, given that ADL state, is 0.2. Assuming away an age effect, if the individual's draw from the uniform distribution is less than 0.2, he is assumed to be admitted to care immediately on the onset of disability and to remain there until he dies. If the draw is greater than 0.2, he never goes into care. If the admission probabilities are then adjusted in Robinson's model to 0.25 (say) for the first 12 months after the onset of a disability, and to 0.16 thereafter, an individual with a draw of 0.22 would be assumed to be institutionalized for 12 months and then discharged, generating some churning. But, these adjustment factors are ad-hoc. Based on the discrepancy with Hurd, Michaud, and Rohwedder, they yield an inadequate degree of churning.[51]

---

[50] Robinson makes several further modifications to his model, including smoothing some outcomes and making an adjustment to reduce the probability of requiring care, based on an analysis of 1994 NLTCS data, which we do not follow.

[51] Hurd, Michaud, and Rohwedder show that one will underestimate lifetime care utilization if one adds up all the episodes of care but omits the period from the final live interview to the date of death. The understatement will be particularly severe if, as in the case of the NLTCS, interviews take place at five-year intervals. This is not a particular concern for the Robinson model because it simulates health and care use histories right up to the date of death. Health is allowed to deteriorate with proximity to death, and as care usage depends on health status, the probability of using care will increase with proximity to death.

Appendix Table 1A. *ADL Limitations by Year – Manton, Gu, and Lamb Definition*

	1982	1984	1989	1994	1999	2004
Nondisabled	73.6%	73.8%	75.2%	76.9%	78.8%	81.0%
IADL only	5.7	6.0	4.5	4.4	3.3	2.4
One or two ADL	6.8	6.9	6.6	6.1	6.3	5.6
Three or four ADL	2.9	3.0	3.7	3.4	3.7	3.8
Five or six ADL	3.5	3.3	3.1	2.9	3.0	3.2
Institution	7.5	7.0	6.9	6.3	4.9	4.0

Note: PNAS weights.

Appendix Table 1B. *ADL Limitations by Year – Robinson Definition*

	1982	1984	1989	1994	1999	2004
Nondisabled	72.0%	70.4%	70.4%	65.9%	66.8%	66.8%
IADL only	12.6	17.8	17.5	19.4	20.9	22.0
One or two ADL	6.3	3.5	3.6	6.8	6.0	5.6
Three or four ADL	1.2	1.0	1.3	1.2	1.0	1.1
Five or six ADL	0.4	0.3	0.3	0.4	0.4	0.5
Institution	7.5	7.0	6.9	6.3	4.9	4.0

Note: PNAS weights.

Appendix Table 2A. *ADL Count Using Alternative Definitions – 1982*

	Manton, Gu, and Lamb							
	0	1	2	3	4	5	6	Total
0	16,294	879	464	268	126	68	84	18,183
1	368	316	256	166	143	107	123	1,479
2	0	25	35	41	63	106	106	376
3	0	0	3	10	30	65	104	212
4	0	0	0	1	2	46	88	137
5	0	0	0	0	1	13	61	75
6	0	0	0	0	0	0	23	23
Total	16,662	1220	758	486	365	405	589	20,485

Source: Authors' calculations.

Appendix Table 2B. *ADL Count Using Alternative Definitions – 2004*

	Manton, Gu, and Lamb							
ADL counts using Robinson's definition	0	1	2	3	4	5	6	Total
0	16,591	540	379	272	141	41	56	18,020
1	177	159	153	146	129	67	62	893
2	0	6	19	28	48	63	58	222
3	0	0	1	5	8	52	75	141
4	0	0	0	0	2	24	87	113
5	0	0	0	0	0	5	66	71
6	0	0	0	0	0	1	43	44
Total	16,768	705	552	451	328	253	447	19,504

Note: Non-institutionalized individuals only.
Source: Authors' calculations.

Appendix Table 3. *Comparison of Codings of Eating ADL*

Stallard disability ranking	Stallard		Manton, Gu, and Lamb		Robinson	
	Classification	Coding	Classification	Coding	Classification	Coding
0	Performs the ADL independently	1a=2, 1b=2	No	1h=1-5, or 1i=1-5, or 8b1=1	No	(1d=1 or 1e=1) and 1g=1
1	Needs help, but does not get help, with the ADL	1a=2, 1b=2	No		No	
2	Performs the ADL with special equipment	1a=2, 1b=1	Yes		Yes	
3	Gets standby help, no equipment	1a=2, 1b=2, 7b=1	No		No	
4	Gets standby help, also uses special equipment	1a=2, 1b=1, 1c=1	Yes		Yes	
5	Gets active help, no equipment	1a=1, 1b=2	Yes		Yes	
6	Gets active help, also uses special equipment	1a=1, 1f=1	Yes		Yes	
7	Unable to perform the ADL.	1a=3	Yes		No	

Source: Authors' analysis of NLTCS codebook; Stallard and Yee (1999); and documents provided by Eric Stallard and Xilaing Gu.

Appendix Table 4. *Care Status of HRS Participants – 2004 Wave Only*

Age	55-59	60-64	65-69	70-74	75-79	80-84	85-89	90-94	95+	All 65+
Males										
Percentages:										
In nursing home at interview	0.0	0.6	0.9	2.4	3.4	7.1	11.7	25.8	42.9	4.9
Any nursing home last two years	0.5	0.8	2.0	4.2	6.7	12.7	19.6	33.4	49.6	8.0
In assisted living at interview	0.0	0.5	0.9	1.4	3.3	2.9	2.6	2.6	7.4	2.3
Any home health care last two year	3.3	4.1	5.7	8.0	11.6	15.4	21.7	30.2	39.9	11.3
Number of:										
Stays last two years	1.00	1.09	1.09	1.31	1.23	1.25	1.12	1.26	1.22	1.22
Nights last two years	25	69	170	173	149	155	137	211	197	163
Females										
Percentages:										
In nursing home at interview	0.1	0.3	1.4	1.7	4.0	8.0	19.7	36.7	55.0	8.2
Any nursing home last two years	0.4	1.4	2.3	5.3	8.6	13.5	27.0	44.7	62.0	12.3
In assisted living at interview	0.0	0.0	0.4	0.9	5.0	1.9	6.6	6.3	2.1	3.3
Any home health care last two year	3.6	5.4	7.0	10.0	12.3	17.8	26.2	33.7	38.1	14.3
Number of:										
Stays last two years	1.06	1.07	1.40	1.32	1.39	1.55	1.88	1.10	1.09	1.44
Nights last two years	159	151	186	129	171	214	303	286	357	249

Note: HRS sample weights. Includes data from exit interviews.
Source: Authors' calculations.

Appendix Table 5. *Parameter Estimates, Health Transition Rates*

	Ending status, j							
Starting status i	1	2	3	4	5	6	7	8
	aij							
1		-2.660	-4.799	-9.090	-4.099	-4.789	-7.502	-3.222
2	-3.487		-1.839	-3.811	-6.673	-3.257	-4.093	-1.952
3	-3.119	-0.629		-1.453	-3.441	-2.376	-9.195	-1.243
4	-9.426	-3.922	-0.607		-0.792	-5.007	-1.218	-2.201
5	-9.794	-2.656	-7.209	-2.101		-9.271	-0.382	0.091
6	-6.788	-2.009	-1.842	-4.848	-6.412		-1.353	-1.778
7	-8.503	-9.161	-7.566	-9.209	0.353	-4.074		-8.308
	bij							
1		0.087	0.087	0.087	0.087	0.087	0.087	-0.612
2	0.037		0.087	0.087	0.087	0.087	0.087	-0.612
3	0.037	0.037		0.087	0.087	0.087	0.087	-0.612
4	0.037	0.037	0.037		0.087	0.087	0.087	-0.612
5	0.037	0.037	0.037	0.037		0.087	0.087	-0.612
6	0.037	0.037	0.037	0.037	0.037		0.087	-0.612
7	0.037	0.037	0.037	0.037	0.037	0.037		-0.612
	cij							
1		8.950	8.950	8.950	8.950	8.950	8.950	1.742
2	-2.019		2.729	2.729	2.729	2.729	2.729	4.482
3	-2.019	-2.019		2.729	2.729	2.729	2.729	4.482
4	-2.019	-2.019	-2.019		2.729	2.729	2.729	4.482
5	-2.019	-2.019	-2.019	-2.019		2.729	2.729	4.482
6	-2.019	-2.019	-2.019	-2.019	-2.019		2.729	4.482
7	-2.019	-2.019	-2.019	-2.019	-2.019	-2.019		4.482
	dij							
1		-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	0.000
2	0.022		-0.004	-0.004	-0.004	-0.004	-0.004	0.000
3	0.022	0.022		-0.004	-0.004	-0.004	-0.004	0.000
4	0.022	0.022	0.022		-0.004	-0.004	-0.004	0.000
5	0.022	0.022	0.022	0.022		-0.004	-0.004	0.000
6	0.022	0.022	0.022	0.022	0.022		-0.004	0.000
7	0.022	0.022	0.022	0.022	0.022	0.022		0.000

Notes: a_{ij} refers to the constant term in equation (1), b_{ij} is the coefficient on gender, c_{ij} is the coefficient on age, and d_{ij} is the coefficient on the time trend. The starting care states *i* 1-7 refer to increasingly poor health states, and the ending care states 1-8 refer to the same increasingly poor health states as well as death. Some coefficients are restricted to take the same value for across some transitions; see text for further details. Bootstrapped confidence intervals indicate that all coefficients are statistically significant at the 99% confidence level or better except for the overall likelihood of transitioning from having two ADLs to dying (a_{58}) the gender differential for the likelihood of health improvement (lower half of b_{ij} matrix) and the time trend for the likelihood of death (last column of d_{ij} matrix)).

Source: Authors' estimates by maximum likelihood.

Recent Working Papers from the Center for Retirement Research at Boston College

SSI at 62: Protecting the Vulnerable When Increasing Social Security's Early Entitlement Age
Norma B. Coe and April Yanyuan Wu, June 2014

Why Do SSI and SNAP Enrollments Rise in Good Economic Times and Bad?
Matthew S. Rutledge and April Yanyuan Wu, June 2014

The Impact of Mandatory Coverage on State and Local Budgets
Alicia H. Munnell, Jean-Pierre Aubry, and Anek Belbase, May 2014

Interest Rates and Economic Growth: Are They Related?
Barry P. Bosworth, May 2014

The Tradeoff Between Health and Wealth in Retirement Decisions
Kristine M. Brown, May 2014

The Effect of Increasing Earnings Dispersion on Social Security Payroll Tax Receipts
Richard Kopcke, Zhenyu Li, and Anthony Webb, May 2014

What Impact Does Social Security Have on the Use of Public Assistance Programs Among the Elderly?
Norma B. Coe and April Yanyuan Wu, May 2014

Differential Mortality and Retirement Benefits in the Health and Retirement Study
Barry P. Bosworth and Kathleen Burke, April 2014

Adding Employer Contributions to Health Insurance To Social Security's Earnings and Tax Base
Karen E. Smith and Eric Toder, April 2014

Lower-Income Individuals Without Pensions: Who Misses Out and Why?
April Yanyuan Wu and Matthew S. Rutledge, March 2014

How Do Subjective Longevity Expectations Influence Retirement Plans?
Mashfiqur R. Khan, Matthew S. Rutledge, and April Yanyuan Wu, January 2014

Impact of the Great Recession on Retirement Trends in Industrialized Countries
Gary Burtless and Barry P. Bosworth, December 2013

All working papers are available on the Center for Retirement Research website (http://crr.bc.edu) and can be requested by e-mail (crr@bc.edu) or phone (617-552-1762).