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RESEARCH ARTICLE

Wealth and the utilization of long-term care services: evidence from the United States

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Abstract
Long-term care (LTC) provision and financing has become a major challenge for policymakers in the United States and worldwide. To inform associated policies and more efficiently allocate LTC resources, it is important to understand how demand for different types of LTC services responds to increased wealth. We use data from the United States Health and Retirement Study to examine the use of LTC services following plausibly exogenous positive shocks to wealth. We further account for time-invariant household-level characteristics, including the expectation of a wealth shock at an unknown future time, by employing household fixed effects. We find that large positive wealth shocks lead to a greater probability of purchase of paid home care but not of nursing home care. Our results imply that expanding home and community-based services and insurance coverage of home care for people without sufficient wealth is likely to be efficient and welfare improving and should be considered by policymakers.

Keywords Wealth effect · Long-term care financing · Nursing home · Home care

JEL Classification I12 · I18 · J14

Introduction

Well-known demographic trends, such as rising life expectancy and aging of the baby boomers, will increase the demand for long-term care (LTC) services in the United States and worldwide (The Center for Insurance Policy & Research, 2016). People with LTC needs generally have chronic conditions and associated functional and/or cognitive limitations that require assistance with activities of daily living (ADLs), such as bathing, dressing, toileting, transferring, and eating; or instrumental activities of daily living (IADLs),

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such as housekeeping, using a telephone, preparing meals, and money management. These types of needs can be served in a variety of settings, for example, at home (formally or informally), in a nursing home, in an assisted living facility, or in an adult day care center, among others. Settings of care do not necessarily represent levels of care, and it is often the availability of financing—not level or type of need—that determines the setting of care (Kane et al., 1998; Stone, 2000).

LTC is expensive in the United States. The national median annual cost is about \$100,000 for a private room in a nursing home and \$50,000 for in-home care (Genworth, 2018). Nationwide, the LTC expenditures totaled \$286 billion in 2016, representing 10 percent of total personal health expenditures (Congressional Research Service, 2018). However, public insurance coverage for LTC is limited. Medicare[1] only pays for short-term rehabilitation in a nursing home but not for long-term chronic care, and Medicaid[2] only pays for LTC if a beneficiary meets strict financial and functional requirements. Due to the high cost and the limited public insurance coverage, LTC is arguably the single largest uninsured health risk facing the country, and only a small number of individuals can finance LTC utilization over an extended period out of pocket (Bernard et al., 2009).

As a result, LTC provision and financing has become a major challenge for policymakers in the United States. To inform associated policies and more efficiently allocate LTC resources, it is important to understand which LTC service(s) individuals are more likely to use if they have more wealth (i.e., the wealth effect). We are particularly interested in the demand responses of nursing home care and paid home care since they are the most common types of paid LTC.

The empirical evidence on wealth effects in LTC utilization is sparse. Goda et al. (2011) find that higher income leads to more use of home care but not nursing home care. Tsai (2015) finds that higher income leads to less use of informal home care provided by children and more use of formal home care. In both papers, to identify causal effects, the estimate of the treatment effect is limited to a narrow range of the older population affected by the Social Security "notch",[3] a low-income group, and it is unclear whether this result generalizes across the income distribution. A recent paper by Costa-Font et al. (2019) studies the exogenous variation in the value of housing assets during the Great Recession and finds that a housing wealth shock exerts a positive and significant effect on the uptake of home health and nursing home entry. However, housing wealth is generally illiquid, and the results may not generalize to other types of wealth.

One key challenge in estimating the effect of wealth on LTC utilization is to account for the potential endogeneity of wealth. That is, household wealth is likely to be endogenous because it tends to correlate with unobservable factors that affect LTC utilization. For example, poor health conditions that are unobservable may lead to both higher LTC utilization and lower wealth, biasing the estimated effect of wealth on LTC utilization. In this paper, we account for this issue by examining the use of LTC services following plausibly exogenous, positive shocks to wealth. Specifically, we exploit the timing of receiving large

[1] Medicare is a federal health insurance program for people who are 65 or older, certain younger people with disabilities, and people with End-Stage Renal Disease.

[2] Medicaid is a federal and state health insurance program for people with limited income and resources.

[3] The Social Security "notch" refers to the difference between Social Security benefits paid to people born between 1917 and 1926 and those born before or after them. The difference resulted from the 1977 amendments to the Social Security Act, which created discontinuities in the calculation for Social Security benefits.

wealth shocks from inheritance, pension settlements, and insurance settlements to study how the receipt of that wealth affects LTC use. Even if a household takes a lifetime view of wealth and may predict whether it will eventually receive wealth from these sources during the life cycle (e.g., an inheritance), the *timing* of the wealth shock is plausibly random and exogeneous for a given household.[4]

Since different types of LTC may respond differently to wealth shocks, we separately examine paid home care use and nursing home use. Specifically, previous studies suggest that home care is usually a preferred LTC setting while nursing home is a setting to be avoided (Goda et al., 2011; Konetzka et al., 2019; Li & Jensen, 2011).

Using the aforementioned wealth shocks and a household fixed-effects model, we examine the within-household variation in LTC utilization over time, comparing periods with wealth shocks to periods without them. We find that positive wealth shocks lead to a greater probability of purchase of home-based LTC but not of nursing home care. These results are robust to a variety of sensitivity checks. These results are consistent with the view in the literature that home health care may be a normal good while nursing home care is an inferior good (Goda et al., 2011; Konetzka et al., 2019; Li & Jensen, 2011). Our results also imply that increased utilization of home care in the presence of insurance could be welfare increasing, which supports the expansion of home-and-community-based Medicaid coverage. Furthermore, finding ways to achieve coverage of home care for people without sufficient wealth is likely to be a prudent public policy for public and private long-term care insurance (LTCI).

Methods

Identification: exogenous wealth shocks

As explained earlier, we identify the effect of wealth on LTC use by exploiting the *timing* of plausibly exogenous, positive shocks to wealth from inheritance, pension settlements, and insurance settlements. Even if a household takes a lifetime view of wealth and may predict accurately whether it will eventually receive wealth from these sources during the life cycle, the *timing* of those shocks is largely out of control of individuals (hence, exogenous within a household). For example, a 70-year old woman may know that she will receive an inheritance when her 95-year old mother dies and that knowledge may affect her consumption patterns on average, including decisions regarding LTC. However, when exactly her mother will die may not be accurately predicted and can be considered random, conditional on the knowledge that her mother would die someday. Therefore, the timing of her inheritance receipt should be largely random within a reasonably limited timeframe. Empirical evidence from the Health and Retirement Study also shows that an individual can hardly accurately predict the receipt, the timing, and the amount of an inheritance, which supports the exogeneity of inheritances.[5] Further, even if an inheritance is accurately

[4] A large number of literature has used inheritances or lottery winnings as exogeneous wealth shocks to study the impact of wealth on economic outcomes (for example, Bø et al., 2018; Brown et al., 2010; Cesarini et al., 2017; Picchio et al., 2018).

[5] The Health and Retirement Study asks questions on respondent's expectation of receiving an inheritance in the next 10 years and the expected amount. By comparing individual's inheritance expectation information in the 2000 survey against their actual inheritance receipt in the 2002–2010 surveys, we find that, among the 4,461 individuals who expected an inheritance in the next 10 years, only 1,082 individuals (24%)

anticipated at some point in the future, it may not significantly change behavior now with respect to LTC utilization because of potential liquidity constraints. In the extreme scenario that the inheritance expectation significantly changes one's LTC consumption and financial planning over his/her lifetime, we would expect the impact of the inheritance shock to be underestimated by our models.

We identify effects of wealth transfers by assessing whether a change in LTC utilization occurs in the wave following the transfer. Conceptually, because we observe most individuals and households at multiple points in time, but these transfers usually occur at just one period of time, each household serves as a control for itself over multiple time periods. By employing household fixed effects, our models account for time-invariant household-level characteristics, including the expectation of a wealth transfer at an unknown future time that could otherwise confound the results.

It is worth noting that these wealth shocks may not be exogenous if the event triggering the wealth shocks also triggers other factors that could impact LTC utilization through a pathway other than increased wealth. For example, insurance settlements may not be exogenous if they are triggered by accidents and those accidents also lead to increased demand for LTC (e.g., a car accident). Although our data do not allow us to examine the causes of insurance settlements, we find no correlation between wealth shocks and ADLs, mitigating this concern. As another example, insurance settlements and inheritance may not be exogenous if they are triggered by the death of a spouse, and if the death of a spouse also affects the respondent's LTC utilization (e.g., loss of an informal caregiver). To test whether that may be the case, we conduct a robustness check excluding individuals whose spouse died recently. We obtain similar estimates using this subsample, suggesting that our results are robust to this alternative pathway. Finally, we conduct two falsification tests: (1) we examine whether hospital care use (among those with insurance for hospital care) responded to the wealth shocks and we find that the wealth shocks has no effect on the hospital care use, mitigating concern that the wealth transfer was associated with a health shock; and (2) we examine the home care and nursing home use in the wave preceding the wealth shocks and we find no difference between people with and without wealth shocks, mitigating concerns that the baseline LTC use is different between these two populations (while controlling for the same set of covariates in our base model). These tests further support a causal interpretation of our results.

Data

Data come from the Health and Retirement Study (HRS), a nationally representative, longitudinal study of individuals over age 50, and the only publicly available, longitudinal, national data set that includes consistently worded questions on LTCI. The HRS consists of five birth cohorts who entered the study in different calendar years. Once they enter the study, respondents are interviewed every two years. We use data from waves 3 to 12 (1996–2014) of members of the Original HRS Cohort (born 1931–1941), the AHEAD

Footnote 5 (continued)

actually received one; and among the 441 individuals who expected an inheritance of \$50,000+, only 97 individuals (22%) received an inheritance of \$50,000+. On the other hand, among the 12,420 individuals who did not expect an inheritance in the next 10 years, 518 individuals (4%) actually received one; and among the 1,125 individuals who expected an inheritance of 0-\$50,000, 118 individuals (10%) actually received an inheritance of \$50,000+. Overall, these findings suggest that the receipt, the timing, and the amount of inheritances are largely unpredictable.

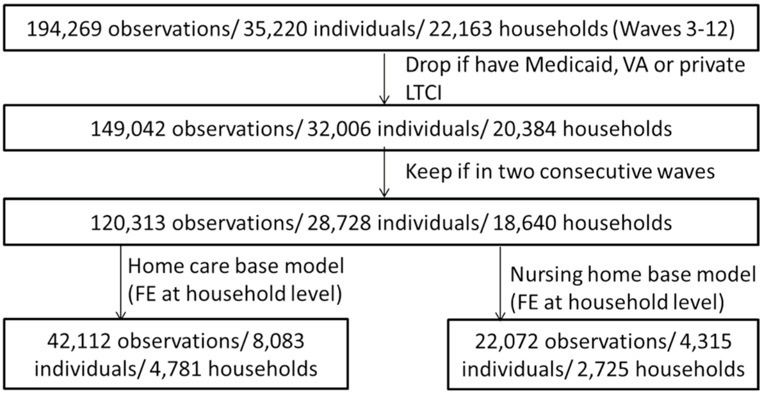

Fig. 1 Deriving the analysis sample

cohort (born prior to 1924), the Children of the Depression Cohort (born 1924–1930), the War Baby Cohort (born 1942–1947), the Early Boomers Cohort (born 1948–1953), and the Mid Boomers Cohort (born 1954–1959). We do not use waves prior to 1996 because the questions related to key variables—for example, whether a respondent had LTCI—were less reliable prior to that year (Finkelstein & McGarry, 2006). We also use RAND-imputed variables for assets, income, and some control variables (RAND Center for the Study of Aging, 2014).

Sample

A schematic diagram of our analysis sample is pictured in Fig. 1. From the combined HRS sample spanning 1996–2014 (194,269 observations), we limit the sample to those individuals who are not covered by the Veteran's Administration (VA), Medicaid, or private LTCI (149,042 observations remaining). This exclusion is intended to isolate the effects of wealth shocks on LTC utilization without being confounded by third-party payment. We also exclude respondents with missing data on key variables or those who did not appear in two consecutive surveys (since the LTC utilization outcome is measured at time t + 1 whereas the other variables are measured at time t). After these exclusions, our analysis sample includes 120,313 observations on 28,728 individuals and 18,640 households.

Further, since we control for household fixed effects and therefore use only within-household variation over time, households that have no variation in the outcome variables are dropped from the analysis when we estimate conditional logit models.[6] This gives us a sample potentially on the margin of LTC use, excluding those who are too healthy to have used LTC at all and those who are so sick that they have used LTC continuously for a long time. After limiting to those marginal households with variations in the outcome, the home care conditional logit model has 42,112 observations on 8083 individuals and 4781 households, and the nursing home conditional logit model has 22,072 observations on

6 We implement our fixed-effects logit model using the conditional logit model. Conceptually, fixed-effects logit model is the same as conditional logit model since the data are grouped and the likelihood is calculated relative to each group.

Table 1 Summary of the analysis sample (by wealth transfer)

Control variables	Home care base model				Nursing home base model			
	No wealth transfer (N = 39,096)	Received $0–$50,000 (N = 2496)	Received $50,000 + (N = 520)	*P* value	No wealth transfer (N = 20,592)	Received $0–$50,000 (N = 1272)	Received $50,000 + (N = 208)	*P* value
Socioeconomic status								
Age	69.8 (10.4)	67.1 (10.1)	65.9 (9.1)	< 0.001	73.5 (10.1)	70.5 (10.2)	70.1 (9.7)	< 0.001
Female (%)	59.2	59.7	58.5	0.833	62.8	62.0	64.9	0.692
Race (%)				< 0.001				< 0.001
White	84.9	87.5	93.3		86.6	88.8	95.7	
Black	12.4	10.5	4.2		11.4	9.2	3.8	
Other	2.8	2.0	2.5		2.1	2.0	0.5	
Hispanic (%)	6.3	3.2	2.3	< 0.001	4.8	3.1	1.0	0.001
Education (%)				< 0.001				< 0.001
Less than HS	24.0	14.7	7.9		25.8	15.0	7.7	
GED	4.5	5.3	2.9		4.0	3.9	3.8	
High school	33.4	31.6	27.5		34.0	33.6	28.4	
Some college	20.8	24.1	31.0		20.8	26.9	27.4	
College +	17.3	24.3	30.8		15.4	20.5	32.7	
Family								
# Children (%)				0.014				< 0.001
0	5.6	5.4	5.4		7.1	5.3	6.7	
1	9.3	8.2	7.9		11.0	8.5	12.5	
2	26.3	26.6	33.1		25.5	25.7	40.4	
3 +	58.8	59.9	53.7		56.4	60.5	40.4	
Married or partnered (%)	71.2	73.5	77.1	0.001	61.1	65.6	64.9	0.004
Has daughter(s) (%)	79.2	79.3	81.0	0.619	78.2	80.8	79.8	0.081

Table 1 (continued)

Control variables	Home care base model				Nursing home base model			
	No wealth transfer (N = 39,096)	Received $0–$50,000 (N = 2496)	Received $50,000 + (N = 520)	*P* value	No wealth transfer (N = 20,592)	Received $0–$50,000 (N = 1272)	Received $50,000 + (N = 208)	*P* value
Children help ADL/IADL (%)	6.1	5.1	3.3	0.005	7.8	6.7	5.3	0.133
Live with children (%)	21.3	21.8	17.1	0.054	16.9	16.4	11.1	0.071
Health								
Self-rated health (%)				< 0.001				0.067
Excellent	9.3	10.0	15.0		8.3	8.3	10.6	
Very good	26.6	29.3	35.6		24.7	26.5	31.3	
Good	33.5	33.3	28.3		33.8	35.1	32.2	
Fair	21.9	19.7	16.9		23.3	22.0	18.3	
Poor	8.7	7.8	4.2		9.9	8.2	7.7	
ADL and memory states (%)				0.192				0.287
No problem	93.0	93.4	95.0		89.9	90.2	90.4	
State 1	3.0	2.9	3.1		4.4	4.0	6.3	
State2	2.7	2.6	1.0		3.7	4.1	1.9	
State3	1.1	0.8	0.8		1.4	0.8	0.5	
State4	0.1	0.2	0.0		0.2	0.3	0.0	
State5	0.2	0.2	0.2		0.5	0.6	1.0	
Diagnosed diseases (%)								
High BP	57.7	52.1	50.0	< 0.001	60.0	55.7	56.3	0.006
Diabetes	20.1	17.5	19.4	0.005	20.8	19.6	24.5	0.239

Table 1 (continued)

Control variables	Home care base model				Nursing home base model			
	No wealth transfer (N = 39,096)	Received \$0–\$50,000 (N = 2496)	Received \$50,000 + (N = 520)	*P* value	No wealth transfer (N = 20,592)	Received \$0–\$50,000 (N = 1272)	Received \$50,000 + (N = 208)	*P* value
Cancer	15.1	15.1	14.8	0.984	15.5	15.6	15.9	0.989
Chronic lung disease	11.0	10.7	9.4	0.454	10.6	10.2	9.6	0.848
Heart problem	27.6	26.4	26.0	0.307	29.5	28.5	26.9	0.519
Stroke	8.5	6.3	6.2	< 0.001	10.7	7.8	8.7	0.003
Psychiatric problem	16.4	19.9	19.2	< 0.001	16.7	18.3	22.1	0.039
Arthritis	64.6	64.8	60.4	0.129	66.7	66.0	63.5	0.555
Wealth (\$)								
Household assets minus wealth shock	485,035 (1,201,996)	621,863 (1,420,112)	1,062,104 (2,036,908)	< 0.001	441,255 (922,963)	560,420 (985,598)	1,322,409 (3,146,904)	< 0.001
Household income minus wealth shock	64,723 (351,671)	77,135 (112,273)	120,723 (174,689)	< 0.001	55,863 (473,430)	64,943 (93,183)	86,819 (94,091)	0.501
Insurance (%)								
Uninsured	6.0	5.9	7.1	0.553	4.3	4.2	5.8	0.570
Medicare	69.3	62.0	53.8	< 0.001	80.9	72.9	66.3	< 0.001

The comparisons across the groups with different wealth transfer status are calculated based on one-way ANOVA (for continuous variables) or chi-squared tests (for categorical variables). Significance of categorical variables calculated as differences among all categories. Standard deviations of continuous variables in parentheses

4315 individuals and 2725 households. Table 1 describes our analysis sample across control variables. For both the home care and nursing home sample, compared to individuals with wealth shocks, individuals without wealth shocks were older; less likely to be White; more likely to be Hispanic; more likely to have lower education; had fewer children; less likely to be married or partnered; more likely to live with children. They were also more likely to have poor self-reported health; more likely to have hypertension and stroke; less likely to have psychiatric problems; had fewer household assets; and more likely to have Medicare. In addition, for the home care sample, individuals without wealth shocks were more likely to be helped by their children for ADLs/IADLs; more likely to have diabetes; and had fewer household income. For the nursing home sample, individuals without wealth shocks were less likely to have a daughter. These differences underscore the need for controlling for these variables and household fixed effects. Appendix Table 5 shows the same statistics for the full sample (194,269 observations).

Key variables

Dependent variables: LTC utilization

We define nursing home and home health use as dichotomous variables indicating use or non-use (i.e., we examine use of LTC services on the extensive margin). The nursing home variable is assigned to 1 if the respondent has been a patient overnight in a nursing home, convalescent home, or other long-term health care facility since the previous wave, and is assigned to 0 otherwise. The home health variable is assigned to 1 if any medically trained person has come to the respondent's home to help him/her since the previous wave, and is assigned to 0 otherwise.[7]

Because HRS questions on LTC do not distinguish the types of the care within nursing home care or home care categories, a challenge in using HRS to examine LTC utilization is separating long-term chronic care that is typically not covered by Medicare (potentially leading to out-of-pocket expenditure) from short-term rehabilitative services that are typically covered by Medicare. Although Medicare covers rehabilitation of up to 100 days in a nursing home following an acute hospital stay with a substantial copayment after the 20th day, in practice the vast majority of stays for this purpose are less than 30 days (Werner & Konetzka, 2018). Therefore, to study the wealth effect, we try to exclude services that are typically covered by Medicare by also defining an indicator for nursing home use of 30 + days as our dependent variable in our sensitivity analysis.

Key independent variable: exogenous wealth shocks

Our key independent variable to capture exogenous wealth shocks is derived from the following HRS question: "People sometimes receive large amounts of money or property in the form of an inheritance, a trust fund, an insurance settlement, and so on. Since (last wave) have you (or your [husband/wife/partner]) received money or property in the form of an inheritance, a trust fund, or an insurance settlement? Have you (or your [husband/

[7] We choose our paid home care variable to be consistent with Goda et al. (2011) and Costa-Font et al. (2019). We acknowledge that this variable may include some care episodes covered by Medicare, which tend to bias our results toward zero.

Table 2 Distribution of wealth shocks

Variables	Home care base model sample (N = 42,112)	Nursing home base model sample (N = 22,072)
Received wealth transfer (%)		
No	92.8	93.3
Received $0–$50,000	5.9	5.8
Received $50,000 +	1.2	0.9
Mean amount of transfer if received ($) (SD)	38,158 (104,971)	35,236 (116,734)
Among recipients, received insurance settlement (%)	26.5	26.4
Among recipients, received pension settlement (%)	1.6	2.4
Among recipients, received inheritance (or trust) (%)	65.6	63.7

[a]The "all kinds wealth transfer" data are from the Rand imputed HRS dataset

[b]The "insurance settlement", "pension settlement" and "inheritance" data are from the original HRS dataset

wife/partner]) received any other large lump sum payments? (Large = $10 k or more)." Follow-up questions probe the dates of transfer, the amount of transfer, and the type of transfer (insurance settlement, pension settlement, inheritance or trust, gift, lawsuit, other). Multiple transfers can be recorded. Because some responses to this question are missing, we use the RAND files, which supply imputations of whether a transfer occurred (lumping all transfers together) and the total amount. Table 2 describes the transfer variable; approximately 7.2 percent of the observations in the home care model and 6.7 percent of the observations in the nursing home model have a wealth transfer. The average amount of transfer for those who received one is approximately $38,158 for the home care model and $35,236 for the nursing home model. All money values are inflated to 2014 dollars using the Consumer Price Index (CPI). In our main model, we use categorical variables for wealth shocks and estimate the impact of receiving a wealth transfer of more than $50,000. We are specifically interested in the impact of receiving a large wealth transfer, such as $50,000, because LTC services (especially nursing home services) are usually expensive, and people are unlikely to change their LTC consumption if they receive small amounts.[8]

Control variables

In all of our models, we control for a rich set of individual and household variables available in the HRS that may affect LTC utilization, such as self-rated health, ADL and memory function status,[9] presence of specific diseases, the linear and quadratic terms of the total household income and assets (with the wealth shock amount deducted), age, sex, race and

[8] The $50,000 threshold is chosen because it is roughly the cost of one year's home care services or half year's nursing home services. A smaller threshold (e.g., $5,000 or $10,000) may not be meaningful given how expensive the LTC services are.

[9] We adapted the ADL & memory status measure from Guo, Konetzka, Magett, & Dale (2014): state 0: no ADL or memory problem; state 1: need help with bathing but no memory problem; state 2: state1 and need help with dressing; state 3: state 2 and need help with toileting and transferring; state 4: state 3 and memory problem; state 5: state 4 and need help with eating.

ethnicity, education, marital status, number of children, Medicare status, and year fixed effects.

Analysis

Using a pooled sample of individuals with at least two consecutive surveys, we specify conditional logit regressions of LTC utilization at time t + 1 on whether the individual *i* in household *h* at time *t* received a small wealth transfer (less than $50,000) or a large transfer (more than $50,000), with no transfer being the reference group:

$$Utilization_{iht+1} = \beta_0 + \beta_1 SmallTransfer_{iht} + \beta_2 LargeTransfer_{iht} + \beta_3 X_{iht} + \beta_4 Year_t + \beta_5 Household_h + \varepsilon_{iht}$$

where the main coefficients of interest are β_1 and β_2. X is a vector of individual- and household-level control variables (as described above in the control variable sub-heading), *Year* is a set of year fixed effects, and *Household* is a set of household fixed effects.

We conduct several robustness checks and sensitivity analyses of our results: (A) We re-estimate the model on the subsample of individuals who reported conditions associated with a greater need for LTC, i.e., individuals who have at least 2 ADLs, 2 IADLs, or cognitive problems.[10] This is to test our assumption that individuals who have stronger needs for LTC have less elastic demand for LTC and are therefore insensitive to a change in wealth (i.e., a smaller wealth effect). (B) Because LTC is expensive and lower-wealth individuals may still struggle to pay for LTC even with a transfer, one might hypothesize that wealthier individuals would be more responsive to a wealth shock. To test this, we include only individuals who have ever been in the top 50 percent of the income distribution (i.e., a wealthier sample). (C) To estimate the general/average wealth effect when receiving a positive wealth shock of any amount, we re-define the transfer variables as a single dichotomous variable indicating whether a wealth transfer of any amount was received. (D) To check for alternative (endogenous) pathways between the cause of the wealth shock and LTC utilization, we exclude individuals whose spouse died between t-1 and t, since their LTC utilization may be affected by the death of the spouse as well as any associated wealth transfer. (E) Lastly, to account for the fact that longer nursing home stays are more likely to require out-of-pocket spending (since they are less likely to be post-acute care and are less likely to be covered by Medicare), we re-estimate the impact of a wealth shock on the probability of nursing home use of 30 + days to focus on long-term chronic care.

In addition, we conduct a falsification test to see whether wealth shocks affect the probability of being hospitalized in the next wave among individuals insured for hospital care using the same household fixed-effects model. Conceptually, due to insurance, we would expect an increase in wealth would not affect the probability of being hospitalized. However, as we discussed above, if the wealth transfer was associated with an event that also affected the respondents' health in a substantive way (e.g., insurance payment associated with a health shock), we may observe increased use of hospital care as well as increased use of LTC following the wealth shock. If this was the case, we would find a positive relationship between wealth shocks and hospitalization. Lack of such a positive relationship mitigates the concern that declining health accompanying positive wealth shocks led to

[10] Most private LTCI policies pay benefits when beneficiaries need help with two or more ADLs or when they have a cognitive impairment. We use the same criteria to define individuals who have greater needs for LTC.

the change in LTC. We also conduct a falsification test to examine home care and nursing home use in the wave preceding the wealth shocks.[11] This test essentially compares LTC use for individuals experiencing a shock against those that do not in the periods preceding the wealth shock. The lack of significant findings supports our identifying assumption that the two populations are comparable.[12]

Results

As shown in Table 3, our main specification estimates a positive and significant effect of a positive wealth shock on the probability of using home health care. The odds of using home health care are 1.362 times higher among individuals experiencing a large wealth shock of $50,000+than their counterparts who did not receive a wealth shock. A small wealth shock of less than $50,000 has a positive but statistically insignificant effect on home health utilization. This is unsurprising because LTC is expensive and likely requires a large wealth shock to change decisions about care. On the other hand, a large positive wealth shock has a negative, small, and statistically insignificant effect on nursing home use.[13] Thus, home health care utilization increases when consumer wealth increases, perhaps because home setting is preferred. The sign of our nursing home estimate may suggest that nursing home may not be a preferred care setting because utilization declines when consumer wealth increases, at least on the margin of individuals who are not too sick to make nursing home care inevitable. However, we should be cautious when interpreting this result since we lack sufficient statistical power.

The results of our sensitivity analyses, exhibited in Table 4, generally support our main results: (A) Consistent with our hypothesis, when we include only individuals who exhibit greater need (and arguably inelastic demand) for LTC, the wealth effect on home health care becomes smaller and insignificant. (B) The results on the wealthier sample are similar to the results on the main sample, suggesting a homogenous wealth effect for individuals in different income groups included in our main sample. (C) For the dichotomous wealth shock model, the odds of using home health care are 1.123 times higher among individuals experiencing any amount of positive wealth shock than their counterparts who did not receive a wealth shock. This effect is statistically significant, and, not surprisingly, is larger than the effect of experiencing a wealth shock of $0-$50,000 but smaller than the effect of experiencing a wealth shock of $50,000+. The effect of receiving any amount of positive wealth shock on nursing home use is still small and insignificant. (D) When excluding individuals whose spouse died between t-1 and t, we obtain similar, though slightly larger, estimates, suggesting that our results are robust to alternative pathways between the cause of the transfer and LTC utilization. (E) When we exclude short-term nursing home use and

[11] For individuals that received multiple wealth shocks, we drop their observations after the first wealth shock.

[12] We control for the same set of variables in this falsification test as in our base model.

[13] One may argue that the $50,000 threshold is still too small for using nursing home care, and the lack of significant findings for nursing home care may be caused by not looking at larger wealth shocks. Therefore, we examined the impact of receiving wealth shocks of $100,000+and $200,000+. Our results show that receiving wealth shocks of $100,000+or $200,000 has a negative but statistically insignificant impact on nursing home use.

Table 3 Odds ratios of receiving wealth transfers on LTC utilization in succeeding wave (base models)

	Any home care	Any nursing home
Wealth transfer (not received is reference)		
Received \$0–\$50,000	1.079	1.017
	(0.946, 1.230)	(0.823, 1.256)
Received \$50,000 +	1.362**	0.740
	(1.041, 1.781)	(0.447, 1.224)
Age	0.914***	0.892**
	(0.872, 0.957)	(0.815, 0.976)
Age^2	1.001***	1.001***
	(1.001, 1.001)	(1.001, 1.002)
Female	0.976	1.047
	(0.900, 1.058)	(0.918, 1.196)
Race (white is reference)		
Black	1.068	1.701
	(0.567, 2.012)	(0.672, 4.306)
Other	0.668**	0.585
	(0.458, 0.974)	(0.298, 1.147)
Hispanic	0.725	0.478
	(0.440, 1.196)	(0.195, 1.169)
Education level (less than HS is reference)		
GED	0.960	0.802
	(0.744, 1.240)	(0.530, 1.212)
High school	0.885	0.833
	(0.763, 1.028)	(0.652, 1.062)
Some college	0.957	0.773*
	(0.807, 1.137)	(0.584, 1.022)
College and above	0.993	0.645***
	(0.812, 1.215)	(0.465, 0.895)
Number children alive (no child alive is reference)		
1 child alive	0.750	1.326
	(0.450, 1.252)	(0.572, 3.074)
2 children Alive	0.674	1.120
	(0.397, 1.143)	(0.467, 2.686)
3 or more children alive	0.584*	0.688
	(0.335, 1.019)	(0.279, 1.699)
Married or partnered	1.424***	1.264***
	(1.267, 1.602)	(1.071, 1.492)
Any daughter alive	1.114	1.375
	(0.789, 1.575)	(0.802, 2.358)
Any child help ADL/IADL	1.576***	1.232**
	(1.397, 1.779)	(1.045, 1.454)
Co-resident with children	0.874**	0.835*
	(0.780, 0.979)	(0.685, 1.017)
Self-rated health (excellent is reference)		
Very good	1.207**	1.058

Table 3 (continued)

	Any home care	Any nursing home
	(1.043, 1.397)	(0.840, 1.332)
Good	1.711***	1.344**
	(1.477, 1.982)	(1.067, 1.692)
Fair	2.370***	1.921***
	(2.028, 2.768)	(1.510, 2.445)
Poor	3.820***	2.739***
	(3.203, 4.559)	(2.094, 3.582)
ADL and memory states (state 0 is reference)		
State 1	1.408***	1.685***
	(1.219, 1.626)	(1.404, 2.024)
State2	1.563***	2.084***
	(1.338, 1.824)	(1.707, 2.545)
State3	1.659***	2.089***
	(1.306, 2.106)	(1.516, 2.881)
State4	1.118	1.797
	(0.523, 2.387)	(0.772, 4.183)
State5	2.135***	4.887***
	(1.232, 3.699)	(2.680, 8.908)
Diagnosed diseases		
High BP	1.137***	0.957
	(1.047, 1.235)	(0.838, 1.094)
Diabetes	1.196***	1.254***
	(1.085, 1.318)	(1.068, 1.473)
Cancer	0.905*	0.956
	(0.814, 1.005)	(0.807, 1.134)
Chronic lung disease	1.457***	1.289***
	(1.297, 1.637)	(1.070, 1.551)
Heart problem	1.050	1.001
	(0.965, 1.143)	(0.875, 1.143)
Stroke	1.165**	1.304***
	(1.034, 1.314)	(1.104, 1.542)
Psychiatric problem	1.036	1.108
	(0.934, 1.149)	(0.948, 1.294)
Arthritis	1.307***	1.075
	(1.200, 1.423)	(0.936, 1.234)
Household assets minus wealth shock in $1000	1.000	1.000
	(1.000, 1.000)	(1.000, 1.000)
(Household assets minus wealth shock in $1000)^2	1.000	1.000
	(1.000, 1.000)	(1.000, 1.000)
Household income minus wealth shock in $1000	1.000	1.001
	(0.999, 1.000)	(1.000, 1.003)
(Household income minus wealth shock in $1000)^2	1.000*	1.000*
	(1.000, 1.000)	(1.000, 1.000)
Uninsured	0.783**	1.037

Table 3 (continued)

	Any home care	Any nursing home
	(0.650, 0.944)	(0.734, 1.464)
Medicare	1.132**	1.043
	(1.002, 1.280)	(0.823, 1.322)
Mean of dependent variable	0.179	0.181
N	42,112	22,072

Results shown are odds ratios from logistic regression models. Numbers in parentheses are 95% confidence intervals of the odds ratios

*$p<.10$; **$p<.05$; ***$p<.01$

define our outcome as nursing home use of 30+days, the effects of positive wealth shocks on nursing home use are still small and insignificant.

The results of our first falsification test, exhibited in Appendix Table 6, show that receiving wealth shocks did not affect one's probability of being hospitalized in succeeding wave. The results of our second falsification test, exhibited in Appendix Table 7, show that receiving wealth shocks did not affect the probability of using home care and nursing home care in preceding wave. These results are consistent with our identifying assumption that the timing of the wealth shocks are exogenous within a household.

Discussion

Using the arguably exogenous timing of positive wealth shocks to individuals, we estimate the effects of wealth on utilization of home health and nursing home services. We find that positive wealth shocks lead to increased utilization of home care but not nursing home care.

These results are consistent with the two prior studies of income effects in this context (Goda et al., 2011; Tsai, 2015), despite key differences in approach. First, these two prior studies examine permanent income shocks whereas our study examines one-time shocks. Second, due to the instrument used in these two papers, their results could only be generalized to low-income, low-education populations. In our analysis, the wealth shocks we exploited generally represented those with higher income and higher education. Third, we exclude individuals who had insurance for LTC (VA, Medicaid, or private LTCI) from our sample whereas these two studies include these people. Compared to individuals without insurance for LTC, those with insurance for LTC are less likely to be affected by positive wealth shocks (i.e., they would have smaller wealth effects) since they do not pay the full price of LTC services. Fourth, since we control for household fixed effects, households that have no variation in the outcome variables are dropped from the analysis. As we discussed earlier, this gives us a sample potentially on the margin of LTC use, excluding those who are very healthy and those who are very sick. These two prior papers do not include household fixed effects in their analysis and do not exclude these households. Given these differences, the similarity of the results is striking and also suggests that the evidence in combination may be applicable to a more general population.

These results have several key implications for policy and the underlying economics of LTC financing. First, individuals are willing to pay for home care out of pocket in the

Table 4 Odds ratios of receiving wealth transfers on LTC utilization in succeeding wave (sensitivity tests)

	Home care model	Nursing home model
Base models		
Wealth transfer (no wealth transfer is reference)		
Received \$0–\$50,000	1.079	1.017
	(0.946, 1.230)	(0.823, 1.256)
Received \$50,000 +	1.362**	0.740
	(1.041, 1.781)	(0.447, 1.224)
Mean of dependent variable	0.179	0.181
N	42,112	22,072
(A) At least 2ADL, 2IADL, or cognitive problems at t		
Wealth transfer (not received is reference)		
Received \$0–\$50,000	1.096	0.993
	(0.918, 1.309)	(0.768, 1.284)
Received \$50,000 +	1.199	0.788
	(0.807, 1.781)	(0.418, 1.486)
Mean of dependent variable	0.246	0.238
N	21,485	13,780
(B) Individuals who have ever been in top 50% income group		
Wealth transfer (not received is reference)		
Received \$0–\$50,000	1.080	0.985
	(0.936, 1.247)	(0.773, 1.255)
Received \$50,000 +	1.359**	0.729
	(1.037, 1.781)	(0.438, 1.213)
Mean of dependent variable	0.159	0.157
N	31,978	15,687
(C) Wealth transfer (binary)		
Received any amount (not received is reference)	1.123*	0.970
	(0.996, 1.267)	(0.796, 1.183)
N	42,112	22,072
(D) Drop if spouse died between t − 1 and t		
Wealth transfer (not received is reference)		
Received \$0–\$50,000	1.072	1.036
	(0.933, 1.232)	(0.824, 1.302)
Received \$50,000 +	1.480***	0.682
	(1.106, 1.982)	(0.392, 1.186)
Mean of dependent variable	0.176	0.178
N	38,376	18,939
(E) Used nursing home for 30 + days		
Wealth transfer (not received is reference)		
Received \$0–\$50,000		1.218
		(0.903, 1.644)
Received \$50,000 +		0.973
		(0.484, 1.958)
Mean of dependent variable		0.184
N		12,610

Results shown are odds ratios from logistic regression models. Numbers in parentheses are 95% confidence intervals of the odds ratios

*$p < .10$; **$p < .05$; ***$p < .01$

presence of a positive wealth shock, if the wealth shock is sufficiently large. Second, we do not see evidence of greater nursing home use with a positive wealth shock. The most plausible explanation for this difference is that nursing homes are not the preferred care setting for wealthier individuals who need long-term care; if not quite an inferior good, it might at least be a last resort. However, there may be other explanations. Admission to a nursing home for long-term care is often permanent, and the wealth shocks we study may not be large enough to affect admission to a nursing home if there is no prospect of ongoing funds to support the high costs. Alternatively, the wealthier group in our sample, when they are sick enough to use institutional care, may use options such as assisted living, not well captured in the HRS. Third, Nyman (1999, 2003) has suggested that moral hazard (i.e., additional use of LTC services caused by gaining LTCI) can be decomposed into two portions: (1) an *inefficient* portion that arises from using a reduction of the price of care to transfer wealth from those who purchase insurance and remain healthy to those who purchase insurance and become ill, and (2) an *efficient* portion that is due to the wealth transfer itself. Our finding that people are willing to pay out of pocket for home care when they receive additional wealth implies that home health care use is likely to be efficient spending. Consequently, insurance that increases access to home care may be socially efficient, and increased utilization of home care in the presence of insurance should be considered welfare-increasing moral hazard.

Overall, our results support the expansion of home and community-based services and suggest that insurance coverage of paid home care (e.g., through Medicaid) may be socially efficient. As policymakers continue to grapple with LTC financing for an aging population, finding ways to achieve coverage of home care for people without sufficient wealth is likely to be prudent.

Appendix

See Tables 5, 6 and 7.

Table 5 Summary of the full sample (by wealth transfer)

Control variables	No wealth transfer (N = 181,008)	Received \$0-\$50,000 (N = 10,751)	Received \$50,000 + (N = 2510)	*P* value
Socioeconomic status				
Age	67.3 (11.3)	64.8 (10.5)	64.0 (9.4)	< 0.001
Female (%)	58.7	58.1	56.9	0.133
Race (%)				< 0.001
White	78.0	85.1	92.6	
Black	16.3	10.4	4.7	
Other	5.7	4.5	2.7	
Hispanic (%)	10.6	5.1	2.6	< 0.001
Education (%)				< 0.001
Less than HS	24.7	13.2	6.5	
GED	4.7	4.5	2.9	
High school	30.4	29.4	25.5	
Some college	21.4	24.7	26.9	
College +	18.9	28.1	38.2	
Family				
# Children (%)				< 0.001
0	7.4	7.2	6.2	
1	10.5	9.2	9.5	
2	25.6	26.7	32.9	
3 +	56.6	56.9	51.4	
Married or partnered (%)	64.1	70.3	74.8	< 0.001
Has daughter(s) (%)	77.5	78.6	77.5	0.026
Children help ADL/IADL (%)	6.4	4.4	2.5	< 0.001
Live with children (%)	25.8	25.6	21.6	< 0.001
Health				
Self-rated health (%)				< 0.001

Table 5 (continued)

Control variables	No wealth transfer (N = 181,008)	Received \$0-\$50,000 (N = 10,751)	Received \$50,000 + (N = 2510)	*P* value
Excellent	10.8	12.5	16.9	
Very good	27.8	31.9	37.7	
Good	31.2	31.5	29.2	
Fair	20.9	16.8	12.2	
Poor	9.3	7.4	4.0	
ADL & memory states (%)				< 0.001
No problem	92.1	94.3	96.8	
State 1	2.9	2.2	1.4	
State2	3.0	2.3	1.1	
State3	1.4	0.9	0.4	
State4	0.2	0.1	0.0	
State5	0.4	0.3	0.4	
Diagnosed diseases (%)				
High BP	55.4	49.5	47.2	< 0.001
Diabetes	19.6	16.4	15.1	< 0.001
Cancer	13.3	13.8	15.0	0.020
Chronic lung disease	10.0	9.7	6.7	< 0.001
Heart problem	23.9	22.3	20.4	< 0.001
Stroke	7.8	5.8	4.8	< 0.001
Psychiatric problem	16.7	17.7	16.2	0.018
Arthritis	57.1	56.1	51.4	< 0.001
Wealth (\$)				
Household assets minus wealth shock	449,301 (1,444,922)	632,643 (1,415,239)	1,053,660 (2,485,959)	< 0.001
Household income minus wealth shock	67,270 (221,184)	88,276 (253,661)	121,645 (206,702)	< 0.001
Insurance (%)				

Table 5 (continued)

Control variables	No wealth transfer (N = 181,008)	Received \$0-\$50,000 (N = 10,751)	Received \$50,000+ (N = 2510)	*P* value
Uninsured	8.2	7.2	5.6	< 0.001
Medicare	57.9	50.2	43.9	< 0.001

The comparisons across the groups with different wealth transfer status are calculated based on one-way ANOVA (for continuous variables) or Chi-squared tests (for categorical variables). Significance of categorical variables calculated as differences among all categories. Standard deviations of continuous variables in parentheses

Table 6 Odds ratios of receiving wealth transfers on hospitalization in succeeding wave (falsification test)

	Hospitalization
Base models	
Wealth transfer (no wealth transfer is reference)	
Received \$0–\$50,000	0.968
	(0.896, 1.046)
Received \$50,000 +	0.918
	(0.786, 1.071)
Mean of dependent variable	0.316
N	77,807

Results shown are odds ratios from logistic regression models. Numbers in parentheses are 95% confidence intervals of the odds ratios

$*p<.10$; $**p<.05$; $***p<.01$

Table 7 Odds ratios of receiving wealth transfers on LTC utilization in preceding wave (falsification test)

	Home care model	Nursing home model
Wealth transfer (no wealth transfer is reference)		
Received \$0-\$50,000	1.084	1.174
	(0.844, 1.393)	(0.895, 1.540)
Received \$50,000 +	1.030	1.052
	(0.594, 1.786)	(0.556, 1.990)
Mean of dependent variable	0.176	0.158
N	23,394	13,369

Results shown are odds ratios from logistic regression models. Numbers in parentheses are 95% confidence intervals of the odds ratios

$*p<.10$; $**p<.05$; $***p<.01$

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Declaration

Conflict of interest None.

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