TIAA Institute

Research Dialogue | Issue no. 229
May 2025

Do misperceptions about Medicare coverage explain low demand for long-term care insurance?

Abstract

Long-term care represents a significant financial risk for elderly individuals. Despite this risk, only 14% of those age 60 and over have private long-term care insurance (LTCI), and about one-third of all long-term care expenses in the United Staes are paid for out of pocket.

In this study, we examine whether misperceptions about Medicare coverage explain the low demand for LTCI. Surveys of older Americans find that about 40% of individuals believe that Medicare will pay for long-term care. However, Medicare only provides limited coverage of short-term stays in skilled nursing facilities following a qualifying hospital stay. Using a regression discontinuity design (RDD) based on eligibility for Medicare at age 65, we document a statistically significant increase in private LTCI coverage rates at the time of enrollment in Medicare. A potential explanation for this increase is that, during the process of enrolling in Medicare, individuals learn that Medicare doesn't cover long-term care services and consequently purchase private LTCI. Using data from two unique surveys on planning for long-term care, we also find that knowledge of Medicare coverage of long-term care services improves at age 65, providing support for the misperception hypothesis.

Padmaja Ayyagari
University of South Florida

Daifeng He
Swarthmore College

Ellen B. Magenheim
Swarthmore College

Jingxin Nie
University of South Florida

Introduction

Long-term care (LTC) represents a significant financial risk for elderly individuals. Estimates suggest that 56% of Americans who survive to age 65 will require LTC services and will, on average, spend $138,000 on such services (Zuraw & Rodriguez, 2021). Despite these risks, only 14% of those age 60 and over have private long-term care insurance (LTCI), and about one-third of all LTC expenses in the United States are paid for out of pocket (Brown & Finkelstein, 2008). Several studies have explored the reasons behind this "LTC puzzle". Brown and Finkelstein (2008) find that Medicaid coverage of LTC services has a large crowd-out effect on private insurance demand. Asymmetric information may also play a role in explaining the LTC puzzle. Individuals may have private information about their risk of needing nursing home care (Finkelstein & McGarry, 2006), and insurance policies usually have high loads (Brown & Finkelstein, 2011). Using a structural model, Ameriks et al. (2016) show that the lack of availability of high-quality LTCI products at least partly explains the low demand for LTCI. Family interactions may also explain the low demand through the availability of informal caregiving or via bequest motives (Bernheim et al., 1985; Kim & Lim, 2015; Lockwood, 2018; Mellor, 2001; Pauly, 1990). Finally, behavioral factors—such as information frictions and limited consumer knowledge about utilization risk, available products and prices, or public insurance coverage—may also explain the low demand for LTCI (Brown & Finkelstein, 2011).

In their work, Brown and Finkelstein (2007) and Brown et al. (2012) raise the possibility that limited consumer information, such as misconceptions about the extent of public insurance coverage, could limit the size of the LTCI market. Surveys of Americans generally find that many older adults are misinformed about the benefits covered by public programs, such as Medicare and Medicaid. For example, Brown et al. (2012) find that 29% of older adults believe that Medicare covers extended LTC use, while a 2007 survey of Americans aged 21 to 75 found that 40% of the respondents believe that Medicare covers the cost of nursing home care for Alzheimer's disease patients (Raphael, 2008). A recent survey by the Kaiser Family Foundation found that 45% of those 65 and older believe that Medicare would pay for nursing home stays if they had a long-term illness or disability (Hamel & Montero, 2023). However, Medicare only covers skilled nursing care for a limited amount of time following a qualifying inpatient hospital stay.[1] It does not cover the long-term use of nursing care that would be necessary for patients with Alzheimer's or other long-term illnesses and disabilities. Since the need for LTC services tends to be low at younger ages, individuals who mistakenly believe that Medicare covers LTC services may rationally decide not to purchase private insurance at younger ages with the expectation that they will be covered by Medicare at older ages when they need such services. Such misperceptions may explain the low private LTCI coverage rates among older adults in the United States.

In this study, we provide the first causal evidence on the role of misperceptions about public insurance coverage of LTC services in explaining demand for private LTCI. We first examine how LTCI coverage rates change at age 65, which is the age most people become eligible for Medicare benefits.[2] Using a regression discontinuity design (RDD), we identify the impact of Medicare eligibility on the probability of having private LTCI. Our hypothesis is that as individuals enroll in Medicare, they learn about the benefits covered by the program, and correct their misperception that Medicare covers LTC services. This learning leads to an increase in their demand for private LTCI. Consistent with this hypothesis, we find a significant, discontinuous increase in LTCI coverage rates at the time of enrollment in Medicare. To further test whether accurate knowledge of Medicare coverage is indeed the pathway leading to an increase in private LTCI coverage at age 65, we use data on knowledge about public insurance coverage of long-term care services from two unique surveys. We find that the proportion of individuals reporting that Medicare pays the most for LTC services decreases significantly at age 65. We also find a significant decrease in the proportion of individuals who agree or strongly agree with the statement that Medicare covers the use of LTC services for those over 65. Together, these findings provide support for our hypothesis that improved knowledge about Medicare coverage leads to the increase in LTCI demand at age 65.

Our study contributes to existing literature on the "LTC puzzle" and, more generally, to the literature on information frictions in insurance markets. While several studies have suggested information frictions as a potential explanation for the "LTC puzzle", there is limited research on the magnitude or nature of such frictions in the U.S. LTCI market. Brown et al. (2012) find that mistaken beliefs about Medicare coverage for LTC services are not correlated with ownership of LTCI in a cross-sectional study. Lumby et al. (2017) find that higher self-rated knowledge of LTCI is correlated with a higher willingness to purchase LTCI, but they do not distinguish between knowledge about public insurance coverage versus knowledge about other relevant factors, such as cost of care or LTCI plan features.

1 Medicare covers skilled nursing facility care following a qualifying inpatient hospital stay for up to 100 days, and a limited set of medically necessary part-time or intermittent home health services.

2 While most people are eligible for Medicare at age 65, persons with disabilities or end-stage renal disease may qualify for Medicare coverage at younger ages.

Ahmadi (2021) finds that underestimation of LTC costs and limited information about underwriting and rejection in the LTCI market lead to a lower purchase rate than under the assumption of full rationality. Brown (2023) finds that a federal-state information campaign encouraging long-term care planning increased LTCI coverage rates among wealthy individuals. A few studies based on other countries also find evidence that knowledge and information frictions are important in explaining demand for LTCI. Boyer et al. (2020) examine both supply- and demand-side factors that may explain low take-up rates in Canadian LTCI markets. They find that awareness of LTCI products and knowledge of LTCI costs and institutional features play an important role, and misperceptions about survival and disability risks play a smaller role. Zhou-Richter et al. (2010) find that low risk perceptions among adult children influence their parents' purchase of LTCI in Germany, where adult children bear financial responsibility when the parent is unable to pay for LTC expenses. The authors find that providing general information about LTC risks increases willingness to purchase coverage.

To summarize, there is some evidence of information frictions playing an important role in private LTCI markets, but most existing studies have focused on knowledge of LTCI products and costs or on risk perceptions. To our knowledge, no study has evaluated whether misperceptions about public insurance coverage are important and whether individuals learn about this coverage as they interact with the public programs. Our study is the first to show that such misperceptions play a small but important role in explaining demand for private LTCI in the United States.

Data

We use data from three surveys: the Health and Retirement Study (HRS), the Survey of LTC Awareness and Planning (SLTCAP), and a survey based on the RAND American Life Panel (ALP) fielded by Brown et al. (2012). The HRS is a biennial panel survey of a nationally representative sample of individuals over age 50 and their spouses.[3] It collects detailed information about respondents' demographics, wealth, health, and insurance coverage. We use 1992–2020 restricted HRS data combined with publicly available data from the RAND HRS Longitudinal File.[4] The restricted HRS data include date of birth and date of interview, which we use to construct the running variable in our analysis (described below).[5] The RAND file provides cleaned versions of commonly used variables such as demographics and insurance coverage. The main dependent variable is a binary indicator for whether the person reports currently having private LTCI. The HRS sample consists of 636,060 person-year observations.

The SLTCAP is a 2014 survey of non-institutionalized adults aged 40 to 70 years old.[6] It was designed to measure older adults' attitudes, knowledge, and experience with LTC services and insurance in the United States. After dropping missing values in key analysis variables, the SLTCAP sample consists of 15,186 observations. The SLTCAP also includes a binary indicator for whether a person has private LTCI or not. More importantly, it asks respondents which government program pays the most for LTC services—Medicare, Medicaid, or the Department of Veterans Affairs. We use this variable to measure the respondents' knowledge about Medicare coverage of LTC services. The ALP surveyed individuals who were 50 years old or older between 2011 and 2013 with a sample size of 1,615.[7] The ALP also includes information on private LTCI coverage. The measure of knowledge in this survey is based on a question asking respondents whether they agree or disagree with the statement that Medicare covers the use of LTC for those over age 65. We use a binary indicator for agreeing or strongly agreeing with this statement as our dependent variable.

Tables 1–3 present summary statistics for the HRS, SLTCAP, and ALP samples, respectively. Column 1 presents results for the full sample, column 2 for respondents younger than 65 years (the control group), column 3 for respondents who are 65 years old or older (the treatment group), and column 4 presents the difference in means for the two age groups. The overall rate of LTCI coverage is 10.3% in the HRS sample, 13.2% in the SLTCAP sample and 22.1% in the ALP sample. The variation in coverage rates across the three samples may be due to differences in the time periods and age groups covered by the surveys. We do find significant differences in coverage rates between the younger-than-65 and the 65-years-or-older groups. In the HRS sample, 13% of respondents who are 65 years old or older have LTCI, while only 7.4% of those younger than 65 years have LTCI.

3 The HRS is sponsored by the National Institute on Aging (grant number NIA U01AG009740) and is conducted by the University of Michigan.

4 Health and Retirement Study, (RAND HRS Longitudinal File 2020(v2)) public-use dataset. Produced and distributed by the University of Michigan with funding from the National Institute on Aging (grant numbers NIA U01AG009740 and NIA R01AG073289). Ann Arbor, MI (2024).

5 Health and Retirement Study, (Respondent Date of Birth and Date of Interview (1992–2020)) restricted dataset. Produced and distributed by the University of Michigan with funding from the National Institute on Aging (grant number NIA U01AG009740). Ann Arbor, MI (2024).

6 Wiener, J. M. (2017). Survey of Long-term Care Awareness and Planning, 2014 [United States]. Inter-university Consortium for Political and Social Research [distributor]. https://doi.org/10.3886/ICPSR36969.v1

7 RAND American Life Panel. Well Being – Long Term Care Insurance, ms186 (2011). Santa Monica, CA: RAND Corporation, 2023.

RAND American Life Panel. Well Being – Long Term Care Insurance V2, ms193 (2011). Santa Monica, CA: RAND Corporation, 2023.

Respondents aged 65 and above are more likely to be male and have less schooling compared with the younger than 65 group. In the SLTCAP sample, 19.2% of respondents aged 65 or over report having LTCI, while only 11.4% of the younger-than-65 group have LTCI. The variables Medicare, Medicaid, Veteran, None, and Don't Know are dummy variables based on responses to the question in the SLTCAP survey about which program pays the most for LTC service. While Medicaid is the correct answer, more respondents chose Medicare (30.9%) or Don't Know (31%) than Medicaid (27.4%) in the full sample. For the age-65-and-above subsample, 33.7% respondents correctly respond that Medicaid is the largest payer. The percentage choosing Medicare as the largest payer of LTC services is 33.6% in the younger-than-65 group and 21.9% in the age-65-and-above group. In the ALP sample, 28.4% of the older group have LTCI compared with 19.5% of the younger group. Overall, 28.9% of respondents agree or strongly agree with the statement that Medicare covers the extended use of LTC for those over age 65. This rate is 32.8% in the younger-than-65 group and 19.4% in the age-65-and-above group.

Empirical methodology

We use a regression discontinuity design (RDD) to estimate the impact of Medicare eligibility on demand for private LTCI. For the running variable, we use age in days calculated using each person's date of birth and date of interview in the HRS sample. Because individuals can begin enrolling in Medicare up to three months before they turn 65, we use the day they are eligible to enroll Medicare as the cutoff for the RDD analysis.[8] Therefore, our analysis captures changes in LTCI coverage at the time of enrollment in Medicare rather than at the time Medicare coverage starts.

The parameter of interest is estimated using a continuity-based RDD approach, which assumes that average potential outcomes are continuous around the cutoff point in the absence of the treatment. We use a local linear regression weighted by a triangular kernel function and the MSE-optimal bandwidth (Cattaneo et al., 2019) for our preferred specification. However, as discussed below, our results are robust to alternative choices of the polynomial function, the kernel function, and bandwidth. The continuity-based approach estimates the following regression using the observations within the optimal bandwidth weighted by a kernel function:

$$Y_{it} = \beta_0 + \beta_1 MedicareEligible_{it} \times EnrollDay_{it} + \beta_2 MedicareEligible_{it} + \beta_3 EnrollDay_{it} + \varepsilon_{it}$$

(Equation 1)

Where $MedicareEligible_{it}$ is a binary indicator for whether person is eligible to enroll in Medicare on interview date (three months before their 65th birthday or later). $EnrollDay_{it}$ is the running variable and represents days to Medicare enrollment eligibility for person i on interview date t. This variable is set to zero exactly three months before a person's 65th birthday (the cutoff point). It is negative before this initial enrollment period starts and positive after it starts. The main dependent variable Y_{it} is a binary indicator for whether person i has private long-term care insurance on date t. The key identifying assumption is that there are no factors, other than Medicare enrollment eligibility, that could lead to a discontinuous change in LTCI coverage rates at the time of enrollment. The RDD parameter of interest is the coefficient on the interaction term.

8 For the sake of brevity, we use age 65 and time of Medicare enrollment interchangeably throughout the manuscript to refer to the cutoff point in the RDD design. However, we use the day individuals can begin enrolling in Medicare as the cutoff point in the HRS sample and the year they turn 65 as the cutoff point in the SLTCAP and ALP samples due to data availability.

The ALP and SLTCAP surveys only include age in years—therefore, we use age 65 as the cutoff. Since age in years exhibits several mass points, we use the local randomization approach to RDD, which is recommended when the running variable is discrete (Cattaneo et al., 2024). The local randomization framework assumes that treatment is as good as randomly assigned within a small window around the cutoff, which allows us to directly compare observations on either side of the cutoff point within this window. Cattaneo et al. (2024) argue that the local randomization approach is more appropriate in cases where the running variable is discrete and continuity-based assumptions are not applicable.

The local randomization RD effect is estimated using the difference between average observed outcomes in the treatment and control groups within a small window W_0:

$$\hat{\tau}^{LR} = \frac{1}{n_{W_{0+}}} \sum_{it:Age_{it} \in W_{0+}} Y_{it}\, 1(Age_{it} \geq 65) - \frac{1}{n_{W_{0-}}} \sum_{it:Age_{it} \in W_{0-}} Y_{it}\, 1(Age_{it} < 65)$$

(Equation 2)

Where $n_{W_{0+}}$ and $n_{W_{0-}}$ are the number of treatment and control units within the window W_0, respectively, and age 65 is the cutoff. W_{0+} represents the set of observations with age greater than or equal to 65 and W_{0-} represents the set of observations with age less than 65. $1(\cdot)$ is the indicator function. The key dependent variables are binary indicators for each response to the question on which public program pays the most for LTC services in the SLTCAP sample and a binary indicator for whether individuals agree or strongly agree that Medicare covers the extended use of long-term care for those over age 65 in the ALP sample. For comparison purposes, we also estimate regressions using an indicator for LTCI coverage as the dependent variable for the SLTCAP and ALP samples. However, our preferred estimate of the effect of Medicare eligibility on LTCI coverage is the estimate using HRS data as it has a much larger sample size and more granular information on age.

We use the data-driven approach suggested by Cattaneo et al. (2024) to choose W_0, which identifies the largest possible window around the cutoff within which predetermined covariates are balanced between the treatment and control groups. We use binary indicators for male and educational attainment to identify this window. The categories in the SLTCAP sample include less than high school, high school, some college, and bachelor's degree or higher. The categories for educational attainment in the ALP sample include high school, some college, and college degree or higher. Inference is based on large sample methods, i.e., the Neyman approach.[9]

9 We also calculated finite sample test statistics using a Fisherian inference approach. Our main conclusions remain unchanged when we do this.

Results

Main findings

As a first step, we examine the change in Medicare coverage at age 65 using the HRS data. We estimate a model similar to Equation 1, where the dependent variable is a binary indicator for being currently covered by Medicare, and the cutoff point is the day on which Medicare coverage starts for individuals who sign up during their initial enrollment period. This is the first day of the person's 65th birthday month (or the first of the month before they turn 65 if their birthday is on the first). Appendix Figure A1 presents the regression discontinuity graph for Medicare coverage. We find a 65.1 percentage point increase in Medicare coverage at this age (significant at the 1% level), which is consistent with the findings of previous studies. For example, Card et al. (2009) finds a 65 percentage point increase in Medicare coverage at age 65 using data from the National Health Interview Surveys (NHIS).[10] Having established that individuals in our sample are significantly more likely to enroll in Medicare once they turn 65, we turn next to the impact on LTCI coverage, which is the main focus of our study.

Table 4 presents the RDD estimates of the impact of Medicare eligibility on LTCI coverage using HRS data, while Figure 1 presents the RDD graph for this analysis. The first row of Table 4 presents estimates using conventional parametric least squares methods. The second row presents bias-corrected estimates, which adjust for misspecification error in the underlying conditional expectation functions, while the third row presents estimates using a robust bias-corrected approach (Cattaneo et al., 2019). Each column in Table 4 presents estimates using a different kernel function. The results in the first column use a triangular kernel, in the second column an Epanechnikov kernel, and in the third column use a uniform kernel. The RDD estimates are quite robust across all these specifications. Using our preferred approach (conventional method and triangular kernel), we find that there is a statistically significant increase of 1.3 percentage points in long-term care insurance rates at the time of Medicare enrollment. This represents a 17.6% increase relative to the mean of the control group (persons younger than age 65). This increase is consistent with our hypothesis that individuals learn about Medicare coverage of LTC services when they enroll in the program and purchase private LTCI as a result.

In Appendix Table A1, we show that our main RDD estimates are robust to several alternative specifications. The first column presents results using a quadratic polynomial regression function. We do not explore higher order polynomials given concerns about overfitting (Gelman & Imbens, 2018). Next, we use a 30-day donut hole RDD (Column 2) and a 90-day donut hole RDD (Column 3) to assess sensitivity to observations near the cutoff.

The fourth column presents results from a specification that adjusts for predetermined covariates. Covariates include gender, race, ethnicity, years of schooling, mother's education, father's education, religion, veteran status, number of children ever born, and place of birth fixed effects. Across all these specifications, we find a statistically significant increase in LTCI coverage rates at the time of Medicare enrollment. Appendix Table A2 shows our RDD estimates are also robust to using alternative bandwidths.

We also use a variety of tests to assess the validity of our identifying assumption that potential outcomes are continuous around the cutoff in the absence of treatment. While it is unlikely that individuals can precisely manipulate the running variable in our application (age), we formally test this using a density test (McCrary, 2008; Cattaneo et al., 2020). The p-value of the density test is 0.5995, which implies that we cannot reject the null hypothesis that observations are continuously distributed around the cutoff. Appendix Table A3 presents results from covariate balance tests, where each covariate is used as the dependent variable in the regression. We use the predetermined covariates described above as none of them should be affected by enrollment in Medicare. If there are significant discontinuities in any of these variables at the time of enrollment, it would suggest that our identifying assumption may not be satisfied. We find that none of the point estimates is statistically significant, which implies that discontinuities in these covariates cannot explain our main results.

As a further test of our identifying assumption, we estimate three placebo regressions (Appendix Table A4). The first two regressions use placebo cutoff points to assess whether the identified effects could be driven by other factors, such as retirement. Since age 65 is a common retirement age for many individuals (Behaghel & Blau, 2012; Deshpande et al., 2020), it is plausible that the increase in LTCI rates is explained by the saliency of financial planning decisions at the time of retirement or other life changes (e.g., moving closer to family or availability of caregiving from family or friends), rather than new information about Medicare coverage. To rule out such alternative explanations, we estimate placebo regressions using age 62 (Column 1) and age 70 (Column 2) as the cutoff points. Age 62 is the earliest age at which individuals may claim Social Security benefits, while age 70 is the age at which delayed retirement credits stop.

10 Interestingly, Card et al. (2009) note that the increase in Medicare coverage at age 65 may be even larger given that Medicare coverage is underreported in the NHIS (Cohen & Martinez, 2005).

Studies have found that retirement rates increase discontinuously at age 62 due to the availability of Social Security benefits (Fields & Mitchell, 1984; Gustman & Steinmeier, 2005; Van der Klaauw & Wolpin, 2008). Therefore, if our main estimates are driven by retirement or other unobserved factors, then we might see significant changes in LTCI coverage rates at these ages. However, if our identifying assumption is correct, we should not see any significant increases at ages 62 and 70. We find no evidence of statistically significant changes in LTCI coverage rates at these ages, suggesting that our main estimates are not driven by retirement or other incentives created by the Social Security program.

For the third placebo regression, we use life insurance coverage as the dependent variable (Column 3 of Appendix Table A4). We expect that new information about Medicare coverage of LTC services should affect demand for LTCI but should not affect demand for life insurance. While Medicare coverage of LTC services is a common misperception, most people do not expect Medicare to provide life insurance. Therefore, an increase in life insurance rates at the time of Medicare enrollment would suggest that other unobserved factors may be driving our estimates, while an insignificant effect would provide support for our identifying assumption. As Appendix Table A4 shows, we do not find any statistically significant changes in life insurance coverage rates at the time of Medicare enrollment. Overall, these analyses provide support for our identifying assumption and show that our main estimates are robust to alternative specifications.

Next, we turn to the results estimated using the local randomization approach and the SLTCAP and ALP samples (Table 5). In the SLTCAP sample, LTCI coverage rates increase by 6.1 percentage points at age 65, which represents a 53.5% increase in coverage rates relative to the control group mean. In the ALP sample, LTCI coverage rates increase by 6.2 percentage points, a 31.8% increase relative to the control group mean. The estimates using these two samples are much larger than the estimates based on the HRS sample, likely because of the differences in the running variable. Recall that the running variable in the SLTCAP and ALP samples is age in years, while the running variable in the HRS sample is age in days. Therefore, the estimates from the SLTCAP and ALP samples represent a year-to-year change in LTCI coverage rates, while the estimate from the HRS sample represents a day-to-day change in LTCI coverage rates. This difference likely explains the much larger point estimates identified using the SLTCAP and ALP samples.

In Appendix Table A5, we present results from covariate balance tests for the SLTCAP and ALP samples. For each covariate and each sample, there is no significant difference in means between the treatment and control groups within the optimal window. The covariate balance test provides support for our identifying assumption that treatment is as good as randomly assigned within the optimal window around age 65.

Knowledge of Medicare coverage

To assess whether improvement in knowledge about Medicare coverage at the time of enrollment accounts for the estimated increase in LTCI coverage rates, we use the knowledge variables available in the SLTCAP and ALP surveys. Table 6 presents RDD estimates for the responses to the question on public insurance coverage in the SLTCAP survey. We find a 6.1 percentage point decrease (an 18.2% decrease relative to the control group mean) in the probability of reporting that Medicare pays the most for LTC services. This estimate is remarkably close to the increase in LTCI rates at age 65 in the SLTCAP sample and suggests that the entire increase in LTCI rates at age 65 may be driven by individuals learning about Medicare coverage of LTC services. We also find a 4.1 percentage point increase (a 16% increase relative to the control group mean) in the proportion of persons reporting that Medicaid pays the most for LTC services, which is the correct answer. There is a 1.1 percentage point increase in the likelihood of reporting that the Department of Veterans Affairs pays the most for LTC services, but this effect is not statistically significant.[11] We also find no significant change in the percent of individuals responding "none" or "don't know" to this question.

In Table 7, we present results using the knowledge variables from the ALP survey. We find a 1.39 percentage point decrease in the probability of agreeing or strongly agreeing with the statement that Medicare covers the extended use of LTC for those over age 65. We find a corresponding increase in the probability of disagreeing or strongly disagreeing with this statement and an insignificant decrease in the probability of neither agreeing nor disagreeing with this statement. Figures 2 and 3 present the RD graphs for the knowledge variables in the SLTCAP and ALP surveys, respectively. The RD graphs for the knowledge variables are considerably noisy and, in some cases, do not show a clear, discrete jump at age 65. For example, the graph for "Medicaid pays the most" shows a discontinuous increase at age 65, but the graph for "Medicare pays the most" suggests that there is a continuous increase in knowledge even within this narrow window. Therefore, while these results suggest that individuals gain better knowledge of Medicare coverage of LTC services at age 65, they should be interpreted with caution.

11 The Department of Veterans Affairs covers LTC services for veterans, but it is not the largest payer of these services.

Heterogeneous effects

In Table 8, we explore whether the estimated changes in LTCI demand vary by demographic, socioeconomic factors, and healthcare needs in the HRS sample. We first examine differences by gender, since studies find that older women have lower levels of financial literacy compared to men, which, combined with longer life expectancy, may make them more vulnerable to old-age poverty (Lusardi & Mitchell, 2008). We do not find substantial differences between men and women in the RDD estimates—for men, LTCI coverage rates increase by 1.4 percentage points at the time of Medicare enrollment, and, for women, this estimate is 1.3 percentage points. The next panel evaluates differences by wealth. Individuals with limited assets may qualify for their state Medicaid program, which covers the extended use of LTC services. Therefore, knowledge of Medicare coverage may not influence the demand for private LTCI among poorer households but may be important for wealthier households. To assess this, we divide our sample into three groups based on the tercile of total household wealth. Although the RDD estimates are imprecise, they are consistent with the hypothesis that wealthier households are more responsive to knowledge about Medicare coverage of LTC services. LTCI coverage rates increase by 1.8 percentage points among households in the highest wealth tercile compared to an increase of 0.7 percentage points among households in the lowest wealth tercile. Next, we examine differences by the availability of informal caregiving. We use the number of living children that the person has as a proxy for the availability of informal caregiving. We do not find substantial differences in the RDD estimates between persons with at least one living child (1.3 percentage points) and persons with no living children (one percentage point). Finally, to explore whether the change in LTCI varies by individuals' expected need for LTC services, we use the self-reported probability of entering a nursing home within the next five years. We find a much larger effect for persons with a 50% or higher subjective probability (2.8 percentage points) than for persons with less than a 50% probability (-0.6 percentage points). However, neither of these estimates is statistically significant at conventional levels.

Conclusion

Our study examines whether information frictions play a role in explaining the low demand for private LTCI among Americans. Using data from the Health and Retirement Study, we find that LTCI coverage rates increase by 17.6% at the time of Medicare enrollment. Using data from two unique surveys, we find suggestive evidence that the increase in coverage at age 65 may be driven by improved knowledge about Medicare coverage of LTC services. These results support our hypothesis that as individuals enroll in the Medicare program, they learn that Medicare does not pay for LTC services, and this knowledge update leads to an increase in demand. Although the estimates are not very precise, we also find larger increases in LTCI coverage rates among wealthier individuals and those with higher expectations of future nursing home use. Given that these individuals likely benefit more from LTCI coverage, these results suggest that some individuals make decisions based on their potential need for care once they have accurate knowledge of Medicare benefits. These findings suggest that informational campaigns or other policies that increase knowledge of public insurance coverage may be effective in increasing demand for private LTCI. However, it is worth noting that while the relative effect is large, the absolute effect is quite small—LTCI coverage rates only increase by 1.3 percentage points at the time of Medicare enrollment. Thus, improved awareness or knowledge is unlikely to drastically increase the size of the private LTCI market in the United States. Future research should explore other policies or solutions to the "LTC puzzle".

References

Ahmadi, A. (2021). *Long-term care insurance: Implications of health uncertainty, misperceptions and suboptimal timing of purchase*. Working Paper.

Ameriks, J., Briggs, J., Caplin, A., Shapiro, M. D., & Tonetti, C. (2016). *The long-term-care insurance puzzle: Modeling and measurement*. (Working Paper w22726). National Bureau of Economic Research. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2850260

Behaghel, L., & Blau, D. M. (2012). Framing social security reform: Behavioral responses to changes in the full retirement age. *American Economic Journal: Economic Policy, 4*(4), 41–67. https://doi.org/10.1257/pol.4.4.41

Bernheim, B. D., Shleifer, A., & Summers, L. H. (1985). The strategic bequest motive. *Journal of Political Economy, 93*(6), 1045–1076. https://doi.org/10.1086/261351

Boyer, M. M., De Donder, P., Fluet, C., Leroux, M. L., and Michaud, P. C. (2020). Long-term care insurance: Information frictions and selection. *American Economic Journal: Economic Policy, 12*(3), 134–69. https://doi.org/10.1257/pol.20180227

Brown, J. H. (2023). The impact of a long-term care information campaign on insurance coverage. *Journal of Health Economics, 92*, 102822. https://doi.org/10.1016/j.jhealeco.2023.102822

Brown, J. R., & Finkelstein, A. (2007). Why is the market for long-term care insurance so small? *Journal of Public Economics, 91*(10), 1967–1991. https://doi.org/10.1016/j.jpubeco.2007.02.010

Brown, J. R., & Finkelstein, A. (2008). The interaction of public and private insurance: Medicaid and the long-term care insurance market. *American Economic Review, 98*(3), 1083–1102. https://doi.org/10.1257/aer.98.3.1083

Brown, J. R., & Finkelstein, A. (2011). Insuring long-term care in the United States. *Journal of Economic Perspectives, 25*(4), 119–42. https://doi.org/10.1257/jep.25.4.119

Brown, J. R., Goda, G. S., & McGarry, K. (2012). Long-term care insurance demand limited by beliefs about needs, concerns about insurers, and care available from family. *Health Affairs, 31*(6), 1294–1302. https://doi.org/10.1377/hlthaff.2011.1307

Card, D., Dobkin, C., & Maestas, N. (2009). Does Medicare save lives? *The Quarterly Journal of Economics, 124*(2), 597–636. https://doi.org/10.1162/qjec.2009.124.2.597

Cattaneo, M. D., Idrobo, N., & Titiunik, R. (2019). A practical introduction to regression discontinuity designs: Foundations. Cambridge University Press.

Cattaneo, M. D., Idrobo, N., & Titiunik, R. (2024). *A practical introduction to regression discontinuity designs: Volume II.* Cambridge University Press.

Cattaneo, M. D., Jansson, M. & Ma, X. (2020). Simple local polynomial density estimators. *Journal of the American Statistical Association. 115*(531), 1449–1455. https://doi.org/10.1080/01621459.2019.1635480

Cohen, R. A., & Martinez, M. E. (2005). Impact of Medicare and Medicaid probe questions on health insurance estimates from the National Health Interview Survey, 2004. *Health E-stats*. National Center for Health Statistics.

Deshpande, M., Fadlon, I., & Gray, C. (2020). *How sticky is retirement behavior in the US? Responses to changes in the full retirement age* (Working Paper w27190). National Bureau of Economic Research. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3603822

Fields, G. S., & Mitchell, O. S. (1984). The effects of social security reforms on retirement ages and retirement incomes. *Journal of Public Economics, 25*(1–2), 143–159.

Finkelstein, A. & McGarry, K. (2006). Multiple dimensions of private information: Evidence from the long-term care insurance market. *American Economic Review, 96*(4), 938–958. https://doi.org/10.1257/aer.96.4.938

Gelman, A., & Imbens, G. (2018). Why high-order polynomials should not be used in regression discontinuity designs. *Journal of Business & Economic Statistics, 37*(3), 447–456. https://doi.org/10.1080/07350015.2017.1366909

Gustman, A. L., & Steinmeier, T. L. (2005). The social security early entitlement age in a structural model of retirement and wealth. *Journal of Public Economics, 89*(2–3), 441–463. https://doi.org/10.1016/j.jpubeco.2004.03.007

Hamel, L., & Montero, A. (2023). The affordability of long-term care and support services: Findings from a KFF survey. *KFF.* https://www.kff.org/health-costs/poll-finding/the-affordability-of-long-term-care-and-support-services/

Kim, H. B., & Lim, W. (2015). Long-term care insurance, informal care, and medical expenditures. *Journal of Public Economics, 125*, 128–142. https://doi.org/10.1016/j.jpubeco.2014.12.004

Lockwood, L. M. (2018). Incidental bequests and the choice to self-insure late-life risks. *American Economic Review, 108*(9), 2513–50. https://doi.org/10.1257/aer.20141651

Lumby, J., Browning, C., & Finke, M. S. (2017). The impact of product knowledge and quality of care on long-term care insurance demand: Evidence from the HRS. *Journal of Personal Finance, 16*(2), 48–61.

Lusardi, A., & Mitchell, O. S. (2008). Planning and financial literacy: How do women fare? *American Economic Review, 98*(2), 413–417. https://doi.org/10.1257/aer.98.2.413

McCrary, J. (2008). Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of Econometrics, 142*(2), 698–714. https://doi.org/10.1016/j.jeconom.2007.05.005

Mellor, J. M. (2001). Long-term care and nursing home coverage: Are adult children substitutes for insurance policies? *Journal of Health Economics, 20*(4), 527–547. https://doi.org/10.1016/S0167-6296(01)00078-9

Pauly, M. V. (1990). The rational nonpurchase of long-term-care insurance. *Journal of Political Economy, 98*(1), 153–168. http://dx.doi.org/10.1086/261673

Raphael, C. (2008). Long-term care: Preparing for the next generation. *The Commonwealth Fund*. https://www.commonwealthfund.org/publications/other-publication/2008/jul/long-term-care-preparing-next-generation

Van der Klaauw, W., & Wolpin, K. I. (2008). Social security and the retirement and savings behavior of low-income households. *Journal of Econometrics, 145*(1–2), 21–42. https://doi.org/10.1016/j.jeconom.2008.05.004

Zhou-Richter, T., Browne, M. J., & Gründl, H. (2010). Don't they care? Or, are they just unaware? Risk perception and the demand for long-term care insurance. *Journal of Risk and Insurance, 77*(4), 715–747. https://doi.org/10.1111/j.1539-6975.2010.01362.x

Zuraw, L., & Rodriguez, C. H. (2021). Caring for an aging nation. *KFF Health News.* https://khn.org/news/article/caring-for-an-aging-nation/

TABLE 1. SUMMARY STATISTICS FOR HRS SAMPLE

	(1) Full sample	(2) Age<65	(3) Age>=65	(4) Difference
Long-term care insurance	0.103	0.074	0.130	-0.0565***
	(0.304)	(0.261)	(0.337)	
Male	0.440	0.411	0.447	-0.0361***
	(0.496)	(0.492)	(0.497)	
Non-Hispanic White	0.653	0.628	0.659	-0.0314***
	(0.476)	(0.483)	(0.474)	
Non-Hispanic Black	0.188	0.196	0.185	0.0103***
	(0.390)	(0.397)	(0.389)	
Hispanic	0.124	0.139	0.120	0.0192***
	(0.330)	(0.346)	(0.325)	
Years of schooling	12.157	12.667	12.018	0.650***
	(3.453)	(3.181)	(3.510)	
Mother’s education	9.510	10.014	9.369	0.645***
	(3.635)	(3.886)	(3.548)	
Father’s education	9.283	9.801	9.139	0.662***
	(3.900)	(4.216)	(3.795)	
Protestant	0.595	0.589	0.596	-0.00762***
	(0.491)	(0.492)	(0.491)	
Catholic	0.268	0.269	0.267	0.00146
	(0.443)	(0.443)	(0.443)	
Veteran	0.196	0.157	0.207	-0.0501***
	(0.397)	(0.363)	(0.405)	
Number of children	2.639	2.518	2.673	-0.155***
	(1.961)	(1.794)	(2.004)	
N	636,060	136,240	499,820	

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Significance levels in Column 4 are based on a t-test of the difference in means between the treatment (>= 65 years) and control (< 65 years) groups.

TABLE 2. SUMMARY STATISTICS FOR SLTCAP SAMPLE

	(1) Full sample	(2) < 65 years old	(3) >= 65 years old	(4) Difference
LTCI coverage	0.132	0.114	0.192	-0.0786***
	(0.00274)	(0.00293)	(0.00671)	
Pays most: Medicare	0.309	0.336	0.219	0.116***
	(0.00375)	(0.00436)	(0.00704)	
Pays most: Medicaid	0.274	0.256	0.337	-0.0807***
	(0.00362)	(0.00403)	(0.00804)	
Pays most: Veteran	0.0449	0.0401	0.0613	-0.0213***
	(0.00168)	(0.00181)	(0.00408)	
Pays most: None	0.0618	0.0550	0.0851	-0.0301***
	(0.00195)	(0.00210)	(0.00475)	
Pays most: DK	0.310	0.313	0.297	0.0157*
	(0.00375)	(0.00428)	(0.00778)	
Male	0.390	0.378	0.430	-0.0522***
	(0.00396)	(0.00448)	(0.00842)	
Less than high school	0.0272	0.0297	0.0188	0.0109***
	(0.00132)	(0.00157)	(0.00231)	
High school	0.155	0.156	0.153	0.00248
	(0.00294)	(0.00335)	(0.00613)	
Some college	0.366	0.369	0.359	0.0100
	(0.00391)	(0.00445)	(0.00816)	
Bachelor or higher	0.451	0.446	0.469	-0.0234**
	(0.00404)	(0.00459)	(0.00849)	
Age	56.96	53.92	67.31	-13.39***
	(0.0671)	(0.0632)	(0.0284)	
N	15,186	11,730	3,456	15,186

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Significance levels in Column 4 are based on a t-test of the difference in means between the treatment (>= 65 years) and control (< 65 years) groups.

TABLE 3. SUMMARY STATISTICS FOR ALP SAMPLE

	(1) Full sample	(2) < 65 years old	(3) >= 65 years old	(4) Difference
LTCI coverage	0.221	0.195	0.284	-0.0894***
	(0.0103)	(0.0117)	(0.0206)	
Medicare pays: Agree	0.289	0.328	0.194	0.134***
	(0.0113)	(0.0139)	(0.0181)	
Medicare pays: Neutral	0.168	0.179	0.142	0.0367*
	(0.00930)	(0.0114)	(0.0160)	
Medicare pays: Disagree	0.544	0.493	0.664	-0.171***
	(0.0124)	(0.0148)	(0.0216)	
Male	0.423	0.407	0.461	-0.0547**
	(0.0123)	(0.0146)	(0.0228)	
Less than high school	0.0241	0.0220	0.0292	-0.00722
	(0.00382)	(0.00435)	(0.00770)	
High school	0.160	0.154	0.175	-0.0213
	(0.00913)	(0.0107)	(0.0174)	
Some college	0.251	0.248	0.259	-0.0106
	(0.0108)	(0.0128)	(0.0200)	
College or higher	0.564	0.576	0.537	0.0392
	(0.0123)	(0.0147)	(0.0228)	
Age	61.20	56.78	71.70	-14.93***
	(0.208)	(0.126)	(0.276)	
N	1,615	1,136	479	1,615

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Significance levels in Column 4 are based on a t-test of the difference in means between the treatment (>= 65 years) and control (< 65 years) groups.

TABLE 4. EFFECT OF MEDICARE ELIGIBILITY ON LONG-TERM CARE INSURANCE COVERAGE (HRS SAMPLE)

	(1) Triangular	(2) Epanechnikov	(3) Uniform
Conventional	0.013^{***}	0.014^{***}	0.014^{***}
	(0.004)	(0.004)	(0.004)
Bias-corrected	0.011^{***}	0.012^{***}	0.012^{***}
	(0.004)	(0.004)	(0.004)
Robust	0.011^{**}	0.012^{***}	0.012^{***}
	(0.004)	(0.004)	(0.004)
N	25,6484	25,6484	25,6484

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The model is estimated using a continuity-based approach. The MSE optimal bandwidth is 2777.1

TABLE 5. EFFECT OF MEDICARE ELIGIBILITY ON LONG-TERM CARE INSURANCE COVERAGE (SLTCAP AND ALP SAMPLES)

	(1) SLTCAP sample	(2) ALP sample
RD estimate	0.0608***	0.0615**
P-value	0.0000	0.0267
Left end of window	61	55
Right end of window	68	74
Effective #obs	4,918	1,098

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The model is estimated using a local randomization approach. Covariates used to determine the optimal window around the age cutoff include binary indicators for male and educational attainment.

TABLE 6. EFFECT OF MEDICARE ELIGIBILITY ON PERCEPTIONS ABOUT PUBLIC INSURANCE (SLTCAP SAMPLE)

Which government program pays the most for long-term care services?

	(1) Medicare	(2) Medicaid	(3) Veterans Affairs	(4) None	(5) Don't Know
RD estimate	-0.0611***	0.0410***	0.0107	0.0085	0.0009
P-value	0.0000	0.0020	0.1059	0.2675	0.9445
Left end of window	61	61	61	61	61
Right end of window	68	68	68	68	68
Effective #obs	4,918	4,918	4,918	4,918	4,918

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Dependent variables are based on responses to the question about which public program pays the most for long-term care insurance in the SLTCAP. The age cutoff is 65 years, and covariates used to determine the optimal window around the age cutoff include binary indicators for male and educational attainment.

TABLE 7. EFFECT OF MEDICARE ELIGIBILITY ON PERCEPTIONS ABOUT MEDICARE COVERAGE OF LONG-TERM CARE SERVICES (ALP SAMPLE)

Medicare covers the extended use of long-term care for those over age 65

	(1) Agree	(2) Neutral	(3) Disagree
RD estimate	-0.1388***	-0.0212	0.1600***
P-value	0.0000	0.3674	0.0000
Left end of window	55	55	55
Right end of window	74	74	74
Effective #obs	1,098	1,098	1,098

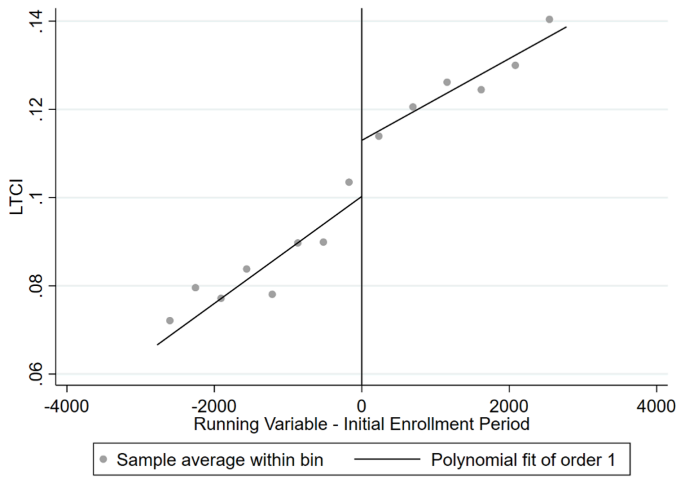
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. The age cutoff for the ALP sample is 65 years. Covariates used to determine the optimal window around the age cutoff include binary indicators for male and educational attainment.

TABLE 8. HETEROGENEOUS EFFECTS (HRS SAMPLE)

	LTCI
Male	0.014**
	(0.005)
N	107,635
Female	0.013**
	(0.005)
N	14,8849
Low wealth tercile	0.007*
	(0.004)
N	84,235
Middle wealth tercile	0.009
	(0.005)
N	84,353
High wealth tercile	0.018**
	(0.007)
N	87,896
Number of living children =0	0.010
	(0.015)
N	18,709
Number of living children >0	0.013***
	(0.004)
N	233,664
Nursing home expectations <50	-0.006
	(0.012)
N	85,022
Nursing home expectations >=50	0.028
	(0.042)
N	16,490

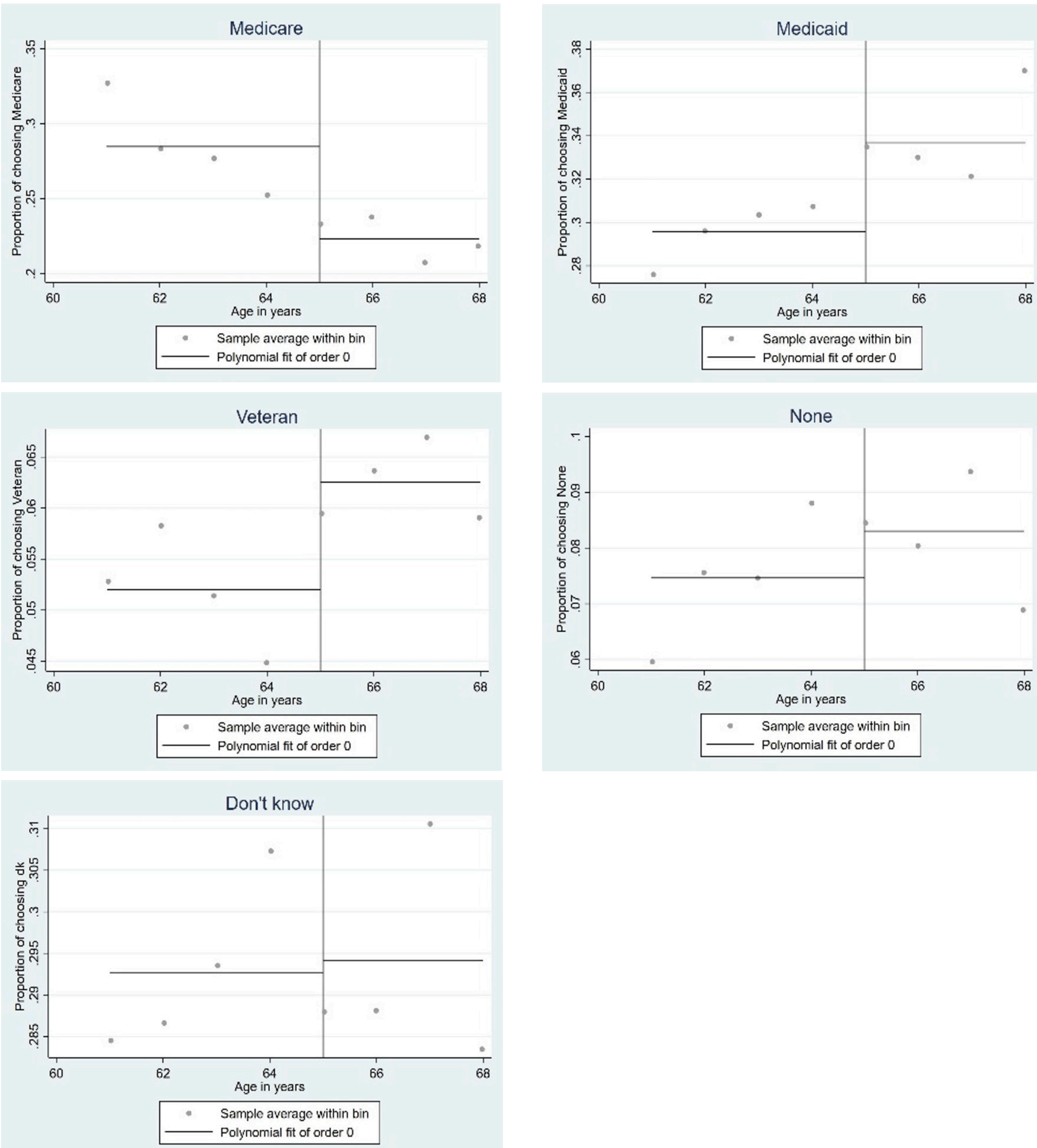
Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

FIGURE 1. REGRESSION DISCONTINUITY GRAPHS FOR LONG-TERM CARE INSURANCE COVERAGE (HRS SAMPLE)



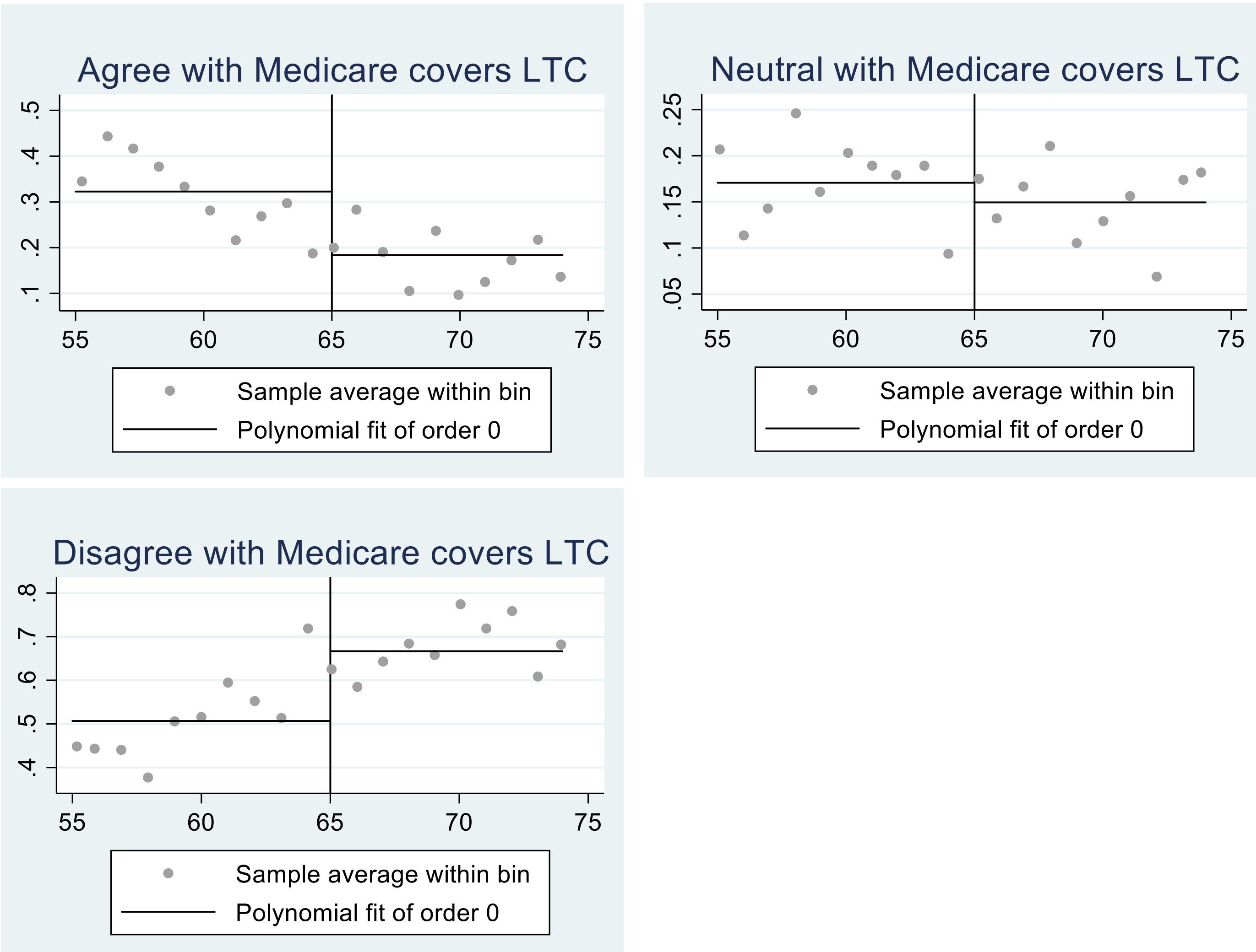
Note: The dependent variable is a binary indicator for LTCI coverage, and the cutoff point is the day on which an individual can begin enrolling in Medicare.

FIGURE 2. REGRESSION DISCONTINUITY GRAPHS FOR PERCEPTIONS ABOUT PUBLIC INSURANCE COVERAGE (SLTCAP SAMPLE)



Note: The age cutoff is 65 years. The dependent variables are dummy variables based on responses to the question about which program pays the most for long-term care.

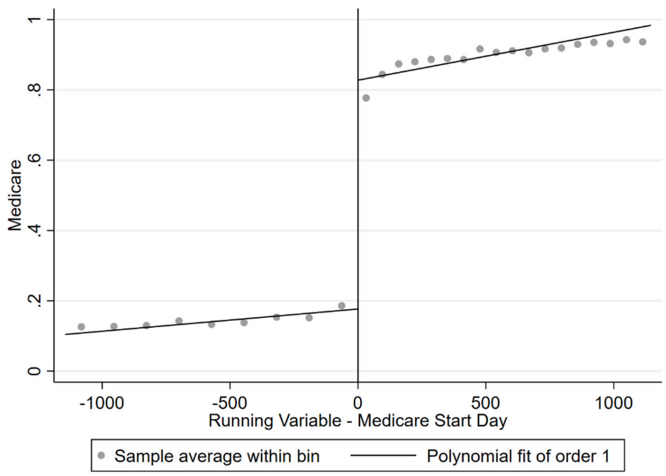
FIGURE 3. REGRESSION DISCONTINUITY GRAPHS FOR PERCEPTIONS ABOUT MEDICARE COVERAGE (ALP SAMPLE)



Note: The age cutoff is 65 years. The dependent variables are dummy variables based on whether respondents agree or disagree with the statement that Medicare covers extended use of long-term care for those over age 65. Responses of agree and strongly agree are combined into a single category as are responses of disagree and strongly disagree. The middle category includes a response of neither agree nor disagree.

Appendix

FIGURE A1. REGRESSION DISCONTINUITY GRAPH FOR MEDICARE COVERAGE



Note: The dependent variable is a binary indicator for currently being covered by Medicare, and the cutoff point is the day on which Medicare coverage starts for individuals who enroll in Medicare within the initial enrollment period.

TABLE A1. ROBUSTNESS TO ALTERNATIVE SPECIFICATIONS (HRS SAMPLE)

	(1) Quadratic polynomial	(2) Donut hole – 30 days	(3) Donut hole – 90 days	(4) Covariates
Conventional	0.011***	0.014***	0.013***	0.011**
	(0.004)	(0.004)	(0.004)	(0.004)
Bias-corrected	0.010***	0.012***	0.011**	0.009**
	(0.004)	(0.004)	(0.004)	(0.004)
Robust	0.010**	0.012***	0.011**	0.009*
	(0.004)	(0.004)	(0.005)	(0.005)
N	256,484	255,160	252,575	206,980

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Covariates include all variables listed in Table 5 and fixed effects for Census region of birth.

TABLE A2. ROBUSTNESS TO ALTERNATIVE BANDWIDTHS (HRS SAMPLE)

	RDD estimates
Bandwidth 2600 days	0.012***
	(0.004)
Bandwidth 2650 days	0.012***
	(0.004)
Bandwidth 2700 days	0.013***
	(0.004)
Bandwidth 2800 days	0.013***
	(0.004)
Bandwidth 2850 days	0.013***
	(0.004)
Bandwidth 2900 days	0.013***
	(0.004)

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A3. COVARIATE BALANCE TEST (HRS SAMPLE)

	RDD estimates
Male	0.004
	(0.007)
Non-Hispanic White	0.004
	(0.006)
Non-Hispanic Black	-0.004
	(0.005)
Hispanic	0.001
	(0.004)
Years of schooling	0.057
	(0.035)
Mother's education	-0.005
	(0.050)
Father's education	0.054
	(0.049)
Protestant	0.000
	(0.006)
Catholic	-0.001
	(0.005)
Veteran	-0.003
	(0.005)
Number of children	-0.025
	(0.020)

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A4. PLACEBO TESTS (HRS SAMPLE)

	(1) Age 62 as cutoff	(2) Age 70 as cutoff	(3) Life insurance
Conventional	-0.003	0.004	0.001
	(0.004)	(0.004)	(0.006)
Bias-corrected	-0.005	0.002	0.004
	(0.004)	(0.004)	(0.006)
Robust	-0.005	0.002	0.004
	(0.004)	(0.005)	(0.006)
N	257,014	257,014	258,396

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$,

TABLE A5. COVARIATE BALANCE WITHIN THE OPTIMAL WINDOW (SLTCAP AND ALP SAMPLES)

	(1) Treatment group mean	(2) Control group mean	(3) Difference in means	(4) p-value
Panel A: SLTCAP sample				
Male	0.4259	0.4087	0.017	0.232
High school	0.1445	0.1352	0.009	0.309
Some college	0.3585	0.3675	-0.009	0.498
Bachelor's or higher	0.4781	0.4747	0.003	0.815
N	2,491	2,427		
Panel B: ALP sample				
Male	0.4454	0.4133	0.0321	0.3620
High school	0.1580	0.1533	0.0047	0.8960
Some college	0.2644	0.2467	0.0177	0.5680
College or higher	0.5517	0.5760	-0.0243	0.5480
N	348	750		

The optimal window is ages 61 to 68 years for the SLTCAP sample and ages 55 to 74 years for the ALP sample. Column 4 presents the Fisherian p-value of a test of difference in means between the treatment and control groups within the optimal window.

About the authors

Padmaja Ayyagari is an Associate Professor of Economics at the University of South Florida (USF). Her research lies at the intersection of health economics and the economics of aging, with a focus on evaluating how social insurance programs and economic shocks influence the health and financial well-being of older adults. Her work has been published in leading academic journals and conference proceedings, including the *Journal of Health Economics*, *Health Affairs*, and *American Economic Review: Papers and Proceedings*.

Daifeng He is a Professor of Economics at Swarthmore College. Her research explores how health policies and programs such as Medicare and Medicaid influence health care utilization among older adults. She has worked extensively on issues related to aging populations, including long-term care insurance and the delivery of long-term care services. Her research has been published in leading peer-reviewed journals, such as the *Journal of Public Economics*, *Journal of Health Economics*, and *Health Services Research*.

Ellen Magenheim is Centennial Professor of Economics at Swarthmore College. Her research focuses on understanding barriers to rational behavior with regard to health, financial, and other types of decisions. She also researches demand and supply factors in health care consumption. Her recent work has been published in *Econometrica*, *Health Affairs*, *Labour Economics*, and *Social Science and Medicine*.

Jingxin Nie is a PhD candidate in Economics at the University of South Florida. His research focuses on evaluating health policies and their impact on health and labor market outcomes. His dissertation examines the effects of Medicaid expansion on workers' compensation, how improved access to mental health services influences health behaviors, and the impact of job loss on cognitive function at older ages.

About the TIAA Institute

The TIAA Institute helps advance the ways individuals and institutions plan for financial security and organizational effectiveness. The Institute conducts in-depth research, provides access to a network of thought leaders, and enables those it serves to anticipate trends, plan future strategies, and maximize opportunities for success.

To learn more, visit tiaainstitute.org.

Join the conversation online: @TIAAInstitute

This research was supported by funding from the TIAA Institute. The content, findings and conclusions are the responsibility of the authors and don't necessarily represent the views of TIAA or the TIAA Institute.

We are grateful to Manan Roy, Sung Choi, Tamara Konetzka, and participants at the Southern Economic Association conference, Southeastern Health Economics Study Group meeting, Florida Workshop on Applied and Theoretical Economics, and American Society of Health Economists conference for helpful comments.

4510358

TIAA Institute

(05/25)