Behavioral Effects of Insurance Coverage and Health Consequences: Evidence from Long-Term Care *

Masaki Takahashi†

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Abstract

How does the generosity of social insurance coverage affect demand for healthcare and health outcomes of elderly people? This paper examines the effects of insurance coverage on long-term care (LTC) utilization and its health consequences using novel administrative data of the public long-term care insurance (LTCI) system in Japan. In LTCI, a recipient's health score determines their insurance coverage limit, and thresholds of the score generate discontinuous changes in the level of coverage limits. I implement a regression discontinuity design and find that the coverage expansion significantly increases recipients' LTC utilization even without changing the prices they face. Moreover, using more LTC has little effect on health outcomes. Together, these results suggest that generous LTCI coverage can induce excessive utilization, mainly because of behavioral biases, without having health benefits.

Keywords: Social insurance, insurance coverage, long-term care, anchoring, heuristic thinking
JEL Codes: D90, D91, I10, I12, I13, I18

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†Hitotsubashi Institute for Advanced Study, Hitotsubashi University, 2-1 Naka, Kunitachi, Tokyo 186-8601, Japan. Email: msk.tkhs@gmail.com

1 Introduction

As the elderly population increases worldwide, providing accessible and cost-efficient healthcare is becoming increasingly important. The social insurance system plays a central role in providing affordable healthcare for elderly people in many countries. And in terms of designing insurance benefits, controlling the generosity of insurance coverage is a key policy tool affecting demand for healthcare. Recipients can obtain subsidies for healthcare up to a level of coverage, although they face payment of the full price for care otherwise. Because of drastic price changes, recipients must invariably use healthcare in consideration of a given coverage. Understanding the effects of insurance coverage on demand for healthcare and its health consequences is crucially important for developing an optimal design of a social insurance system.

The basic concept of moral hazard in health insurance assumes that insurance coverage affects a recipient's demand for healthcare only through price.[1] It then makes the strong prediction that only a recipient facing price changes would respond to coverage changes. This prediction also implies that if most recipients' demand for healthcare is well within (or outside) a given coverage, then the effect of modest coverage changes might be slight because the associated price changes influence a small fraction of recipients. Demand for healthcare is generally so diverse that it is unlikely that a large percentage of recipients would be affected simultaneously by a particular coverage change directly through price. This being the case, the policy effects of coverage changes might be quite small.

When an individual's behavioral biases are considered, the effects of changes in insurance coverage might be much greater than that predicted by standard economic theory. Some behavioral models suggest that even recipients who do not face effective price changes might respond to coverage changes. A couple of well-established behavioral biases are related to this context: anchoring effects and heuristic thinking. Recipients might respond to coverage changes even though it is irrelevant to rational decision-making if they regard insurance coverage as an initial cue in judgment (psychological anchor). Similarly, if recipients make their demand level a certain ratio of coverage through heuristic thinking, then coverage changes affect their demand without changing the price

[1] Here, price means not only a "spot" price but also a "future" price an individual would face in intertemporal dynamic decision-making. Aron-Dine, Einav, Finkelstein, and Cullen (2015) explains the importance of considering effects of future price on individual decision-making in a nonlinear pricing setting. Einav and Finkelstein (2018) present a comprehensive literature review of moral hazard in health insurance.

they face. The policy implication of insurance coverage depends crucially on whether these behavioral biases exist because they imply that any recipient might be affected by changes in insurance coverage, not merely those who face price changes. Therefore, examining the behavioral biases associated with insurance coverage is fundamentally important to assess the potential effects of insurance coverage on healthcare demand.

This paper presents how the generosity of insurance coverage affects demand for health-related services and health outcomes of elderly people, considering their behavioral biases. Despite the numerous and diverse implications for insurance design, little is known about the economic and health effects of behavioral biases associated with insurance coverage. To address this issue, I study behavioral responses to insurance coverage and its health consequences in the context of a large social insurance program: the long-term care insurance (LTCI) system in Japan. LTCI coverage is characterized by a monthly coverage limit that sets the monthly maximum spending on home-based long-term care (LTC) services that can be covered by insurance. A unique feature of LTCI is that the coverage limit for recipients who use home-based care is determined by a single health index (standardized care time), which reflects how much LTC the recipient needs. Every LTCI recipient must take a nationally-standardized health survey that determines their own standardized care time and the coverage limit they will receive. Recipients must regularly retake the survey; they receive a newly designated coverage limit each time.

Using newly available administrative data on LTCI, I implement a regression discontinuity (RD) design to estimate the effects of insurance coverage generosity (monthly coverage limit) on LTC utilization. I take advantage of five thresholds of standardized care time, which creates discontinuous variation in coverage limits for home-based care. Although the RD estimates explicitly show that generous insurance coverage leads to an increase in LTC utilization, this empirical strategy has a limitation on how to interpret the estimates. It can only provide estimates of "overall effects" of insurance coverage and cannot determine the extent to which they result from "behavioral effects" caused by behavioral biases or "price effects" resulting from rational responses to price changes.

To identify behavioral effects, it is necessary to examine whether recipients who do not face effective price changes respond to coverage changes. For instance, coverage expansion does not change the price for recipients who do not exhaust insurance coverage. The advantage of using

LTCI in this analysis is that monthly utilization is subject to the recipient's predetermined plan. It can be regarded as static decision-making. Therefore, coverage changes are less likely to affect recipients' utilization through their rational forward-looking behavior such as a precautionary motive. I implement the RD design with a set of recipients whose utilization has been sufficiently lower than a given coverage limit to identify behavioral effects. The identification strategy is enabled by coverage changes resulting from a periodic re-examination of standardized care time and subsequent reclassification. Specifically, I first collect recipients whose monthly LTC utilization is less than half the monthly coverage limit ("low-demand" recipients). This set of recipients is then narrowed further to those whose coverage limit in the next term is either unchanged or one step higher than the earlier one. This procedure allows for implementation of an RD design to estimate the behavioral effects of coverage expansion for those who do not face effective price changes. Similarly, I estimate effects of coverage expansion on recipients who exhaust insurance coverage ("high-demand" recipients) and then compares effects on these two groups.

The RD estimation focusing on low-demand recipients reveals that recipients are affected strongly by behavioral effects of coverage expansion. Importantly, the magnitude of behavioral effects varies among recipients with different health conditions. Behavioral effects are statistically significant for recipients with less-severe health conditions: a one-unit expansion of insurance coverage increases LTC utilization by 0.2-0.3 units for those affected by behavioral effects. In contrast, recipients with severe health conditions are not influenced by behavioral effects; estimates for these recipients are statistically not significant. Although the RD estimates show that the effect of coverage expansion on low-demand recipients is smaller than on high-demand recipients, the overall effect of coverage expansion is attributed mainly to behavioral effects because most recipients do not exhaust insurance coverage.

The welfare implications of insurance coverage depend crucially on the health consequences. Therefore, I examine the influence of home-based LTC on health outcomes. I use the thresholds generating discontinuous changes in insurance coverage as instruments for service utilization. A recipient's standardized care time and service usage during the next certification term are used as health outcomes proxies because this information is expected to reflect recipient's needs for LTC. The RD estimates show that, for both preventive and usual care, using more LTC affects health outcomes only slightly. This result suggests that generous insurance coverage can induce excessive utilization of LTC from the perspective of recipients' health.

This paper is related primarily to a growing body of literature elucidating individual decision-making under nonlinear price schedules of health insurance, especially Medicare Part D program for prescription drugs (Aron-Dine, Einav, Finkelstein, and Cullen, 2015; Einav, Finkelstein, and Schrimpf, 2015, 2017; Kowalski, 2015; Abaluck, Gruber, and Swanson, 2018; Dalton, Gowrisankaran, and Town, 2019). Insurance coverage with a coverage limit such as LTCI in Japan can be interpreted as having a nonlinear price schedule because individuals face different prices for the same goods depending on whether they are within or outside of specific coverage. Baicker, Mullainathan, and Schwartzstein (2015) discuss the welfare consequences of "behavioral hazard" in health insurance. Recent studies of Medicare Part D also highlight the behavioral biases associated with nonlinear pricing. Particularly, Abaluck, Gruber, and Swanson (2018) find that low-spending beneficiaries who have fundamentally zero probability of reaching the coverage gap nonetheless respond to filling the coverage gap. It is noteworthy that the literature generally attributes behavioral biases to a complex and dynamic decision-making environment. In contrast, this paper finds that even in a simple static decision-making environment, insurance coverage strongly induces behavioral biases. This result suggests that behavioral biases associated with insurance coverage are indeed prevalent. It also highlights the importance of considering non-standard decision-making to achieve optimal insurance design. Another important contribution to these studies is that I examine the health consequences of a nonlinear price schedule, whereas earlier studies have exclusively focused on the effect on individual economic behavior.

This paper is also related to the literature on behavioral biases such as anchoring and heuristic decision-making. Anchoring effects are prevalent in many decision-making contexts: in annuity plans (Bernheim, Fradkin, and Popov, 2015), savings (Choi, Haisley, Kurkoski, and Massey, 2017), credit spreads (Dougal, Engelberg, Parsons, and Van Wesep, 2015), art auctions (Beggs and Graddy, 2009), and real estate transactions (Bucchianeri and Minson, 2013). Heuristic thinking has also been shown to exist in important decision-making contexts such as the purchase of cars (Lacetera, Pope, and Sydnor, 2012) and the repayment of debt (Gathergood, Mahoney, Stewart, and Weber, 2019). Regarding healthcare, Coussens (2018) demonstrates that heuristics are used in physicians' diagnostic decision-making. This study extends the literature to demonstrate that these behavioral biases also strongly affect decision-making in social insurance programs.

Additionally, this study contributes to the literature examining the health effects of LTC. Whereas the effects of nursing home quality on health outcomes has been studied extensively in the health economics literature (Lin, 2014; Foster and Lee, 2015; Kim and Lim, 2015; Friedrich and Hackmann, 2018), home-based care has not acquired much attention despite its growing importance. A notable exception is work by Kim and Lim (2015), which studies subsidy effects for home-based care and institutional care on medical expenses using the LTC insurance system in South Korea.[2] They find that incentivizing transitions from facility to home care can reduce medical expenses. Some medical studies also explored effect of home-based care on health outcomes. For example, Gill *et al.* (2002) report an experiment that randomly assigns elderly people to a home-based intervention program to examine the health consequences of the program. They find that people who are assigned to the program exhibit less functional decline over time. Although the literature mainly examines effects of the extensive margin of home-based care, this study sheds light on an intensive margin of home-based LTC for recipients with various health conditions. I find that using more LTC has little effect on health outcomes, irrespective of health condition of recipients.

The remainder of the paper is presented as follows. Section 2 presents the institutional background and discusses the expected effects of insurance coverage on LTC utilization. Section 3 describes LTCI administrative data and presents summary statistics. Section 4 explains empirical strategies applying RD design. Section 5 reports estimation results for the effect of insurance coverage on LTC utilization and its health consequences. Section 6 discusses some policy-relevant topics of the behavioral response to insurance coverage. Section 7 concludes this paper.

2 Background and Framework

2.1 Public Long-Term Care Insurance in Japan

The social insurance system for LTC in Japan, arguably the most radical change in the Japanese healthcare system in decades, was established in 2000. Long-term care insurance (LTCI) allows eligible recipients to choose LTC services from among various alternatives and to use them with a moderate out-of-pocket payment according to specific coverage. Because of rapid aging of the

[2] Kim and Lim (2015) also examine subsidy effects of formal home and institutional care on LTC utilization and informal care use. In this paper, I study the influence of insurance coverage for home-based care on LTC utilization and reveals that the main driver of behavioral responses to insurance coverage are behavioral biases rather than price changes.

population, spending on LTCI has increased rapidly. It has come to account for a substantial fraction of Japanese national finance. The total cost of LTCI, which was 3.6 trillion JPY (36 billion USD,[3] 0.7% of Japanese GDP) in 2000, amounted to 10.8 trillion JPY (108 billion USD, 2.0% of Japanese GDP) in 2017.[4] The cost is expected to continue increasing in the years and decades to come.[5]

LTCI is a mandatory social insurance system in which people of a particular age group must participate. People aged 65 and older are classified as "first-insured" and those between ages 40 and 64 as "second-insured." They have to pay premiums set by their municipal government, but second-insured individuals must present with designated diseases to receive insurance benefits.[6] Second-insured people are younger, with additional eligibility requirements. Therefore, most LTCI recipients are first-insured.[7]

Care-Needs Certification

Several steps are necessary before one receives LTC services under LTCI. Figure 1 depicts the LTCI utilization process. The first step is to apply to a municipal government for the "care-needs certification," which is a health survey to assess applicant need for LTC.[8] The main purpose of care-needs certification is to classify applicants into specific "care-needs levels" that determine the available services and insurance coverage. Care-needs certification is based on a nationally-standardized face-to-face survey conducted by a trained examiner at an applicants' home (or at a hospital if applicants are hospitalized). The examiner first checks 79 items related to the applicant's physical and mental condition. Based on the checkup results, a special formula generates hypothetical care times for eight categories of assistance. Table 1 presents the possible time ranges

[3] For simplicity, I use an exchange rate of 100 JPY = 1USD throughout this paper.

[4] Ministry of Finance. URL: https://www5.cao.go.jp/keizai-shimon/kaigi/special/reform/wg1/291108/shiryou1-8.pdf (Japanese)

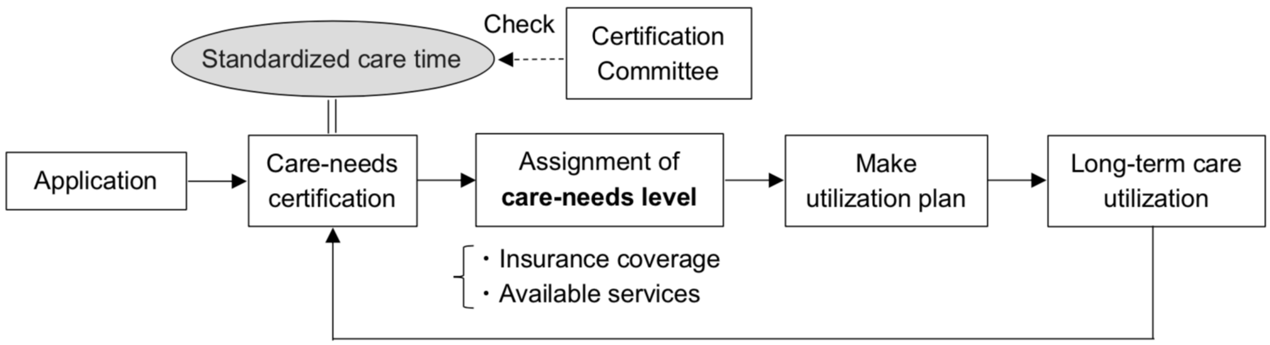
[5] Based on a prediction made by the Cabinet Office, the total cost of LTCI is expected to reach 25 trillion JPY (250 billion USD) in 2040. URL: https://www5.cao.go.jp/keizai-shimon/kaigi/minutes/2018/0521/shiryo_04-1.pdf (Japanese)

[6] Designated diseases include terminal cancer, rheumatoid arthritis, ALS, ossification of posterior longitudinal ligament, osteoporosis, dementia, Parkinson's disease, spinocerebellar degeneration, spinal canal stenosis, progeria syndrome, multiple system atrophy, diabetes, cerebrovascular disease, arteriosclerosis obliterans, chronic obstructive lung disease, and osteoarthritis.

[7] In 2017, first-insured recipients account for 96.4% of all recipients. URL: https://www.mhlw.go.jp/topics/kaigo/osirase/jigyo/m17/1712.html (Japanese)

[8] A family member or guardian can also apply for the care-needs certification on behalf of the recipients.

Figure 1: Utilization Process of Long-Term Care Services under LTCI



for each category. The sum of these care times is the “standardized care time,” which reflects how much LTC the applicant needs. The longer the standardized care time is, the more an applicant is regarded as needing LTC. This indicator serves a key role in determining the insurance coverage for each applicant.

Next, based on the standardized care time, applicants are assigned tentatively to a corresponding care-needs level. Table 2 presents a range of standardized care time and a corresponding care-needs level. After the tentative assignment, the Certification Committee of Needed Long-Term Care (hereinafter, the Certification Committee), which consists of physicians, nurses, and other health and social service experts, assesses whether the standardized care time appropriately reflects the applicant’s need for LTC. If the care time is regarded as appropriate, then the applicant is assigned to the relevant care-needs level; if not, then the Certification Committee reassigns the applicant to the proper care-needs level.

Table 1: Category of Assistance and Range of Time Length

Category of assistance	Range of time length (minutes)
Eating	1.1 – 71.4
Transferring	0.4 – 21.4
Toileting	0.2 – 28.0
Hygiene	1.2 – 24.3
Housework	0.4 – 11.3
Dementia	5.8 – 21.2
Exercise	0.5 – 15.4
Medical care	1.0 – 37.2
Standardized care time	10.6 – 230.6

Table 2: Monthly Coverage Limits for Each Care-needs Level

Care-needs level	Standardized care time	Coverage limit (unit)
(Not eligible)	< 25.0	—-
Support level 1	25.0 – 31.9	5,003
Support level 2	32.0 – 49.9	10,473
Care level 1	32.0 – 49.9	16,692
Care level 2	50.0 – 69.9	19,616
Care level 3	70.0 – 89.9	26,931
Care level 4	90.0 – 109.9	30,806
Care level 5	≥110.0	36,065

Available Services and Coverage Limits

Care-needs levels are divisible into two broad categories, which are "Care level" and "Support level." These broad categories designate the LTC services available to recipients. Those who are classified as Care level are deemed to need LTC to conduct their daily lives. These recipients are allowed to use widely various LTC services. In contrast, people classified as Support level are considered able to perform normal daily activities on their own. Consequently, the available services under the Support level are aimed at preventing recipients from having an increased need for care in the future.[9] The prices of LTC services are fixed by the government in both categories and are adjusted every three years.

A distinct feature of LTCI is that insurance coverage for recipients who select home-based care is determined by the recipient's assessed care-needs level. Recipients are therefore unable to choose their coverage on their own based on their preferences. The insurance coverage of LTCI is characterized by monthly coverage limits.[10] For LTC up to the monthly coverage limit, recipients pay 10 or 20 percent of the total expenditure (depending on income), after which the recipient pays the full price.[11] Table 2 presents the coverage limit for each care-needs level expressed as a total unit value for LTC services. Although the unit value varies slightly across services and

[9]Long-term care under the Support level is designed to help recipients accomplish everyday activities independently. For example, if a recipient has a lack of hand mobility, then the caretaker's role is to design a method for housework that the recipient can perform independently.

[10]As described herein, the terms "insurance coverage" and "coverage limit" are used interchangeably.

[11]The 20 percent coinsurance, introduced into 2015, applies to individuals with total annual income of more than 1.6 million JPY (16K USD); that of first-insured family members is greater than 3.46 million JPY (34.6K USD), or 2.8 million JPY (28K USD) for a single-person household).

municipalities, a reasonable approximation of unit value is 10 JPY or about 0.1 USD. Appendix Figure A1 portrays out-of-pocket expenditures as a function of total expenditures on LTC services when the coinsurance rate is 10 percent. Table 2 also shows that recipients who belong to the higher care-needs level (i.e. those who have a severe condition) are entitled to more generous coverage. They are classified into either Support level 2 or Care level 1 if applicants' standardized care time is between 35 and 49.9 min. This allocation procedure draws on specific items of standardized care time representing the applicants' cognitive ability and vulnerability in health status.[12]

Long-Term Care Utilization

After available services and insurance coverage are determined, recipients who select home-based care create a monthly plan ("care plan") indicating when and what services are to be provided. In most cases, recipients produce a detailed care plan assisted by specialist, called care manager.[13] The care manager is also responsible for monitoring the recipient's living conditions to ascertain whether the care plan continues to fulfill the recipients' needs. If the care plan becomes unsuitable because of, for example, changes in health condition, then recipients may make changes to the plan on a monthly basis.[14] This type of LTC utilization scheme based on a care plan therefore requires recipients to make a static decision each month about the LTC services they will receive. Another important matter to note is that no unused portion of the monthly coverage limit can be carried over to the next month. In other words, recipients cannot expand future coverage by underuse of current services. This institutional feature also guarantees that LTC utilization can reasonably be interpreted as static decision-making rather than dynamic forward-looking decision-making.

To accommodate changes in LTC needs, recipients must take care-needs certification regularly. They are reclassified into different care-needs levels if necessary. In principle, the first care-needs certification is valid for a half year. The following certification is valid for one year. Recipients must retake the care-needs certification before the term expires to continue using LTC services

[12] Recipients are classified into Care level 1 if both of the following requirements are satisfied: (1) It is difficult for the recipient to understand how to use care prevention services appropriately because of mental disability. (2) The physical and mental condition of the recipient is likely to worsen in a short period.

[13] According to the Long-Term Insurance Act, a care manager is defined as an expert who has specialized knowledge about LTC who helps recipients draw up the best care plan based on their needs, in coordination with LTC providers and the municipal government.

[14] In practice, LTC utilization should be regarded as joint decision-making by the recipient, family member, and care manager. For simplicity, the term "recipient" is used as decision-maker throughout this paper.

under LTCI. Hereinafter, I use “certification term” or just “term” to represent each valid term of the care-needs certification.

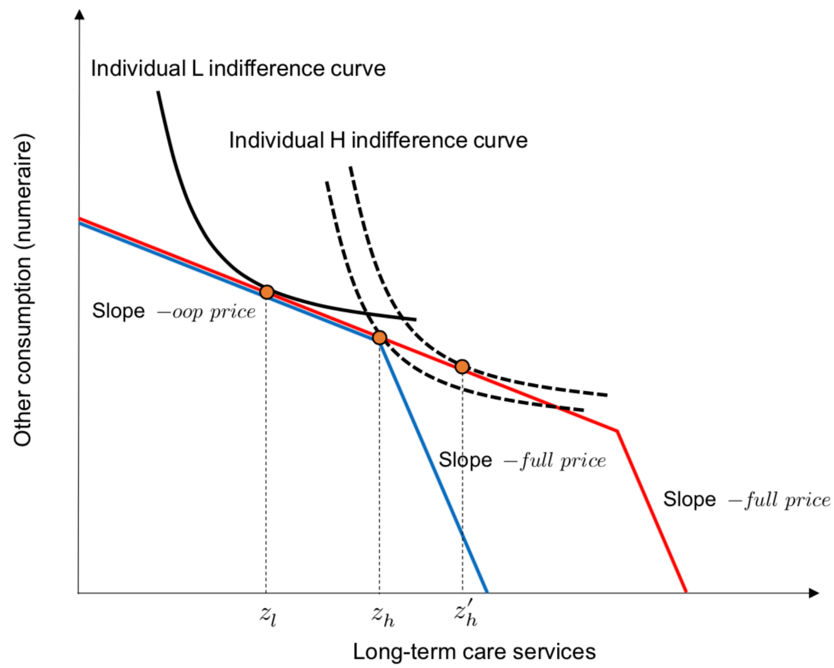
2.2 Mechanisms of Recipients’ Responses to Insurance Coverage

Discussions of moral hazard related to health insurance assume that price is the only channel through which insurance coverage affects demand for healthcare. Figure 2 depicts a simple mechanism of recipients’ responses to insurance coverage under the typical moral hazard framework. In keeping with the structure of decision-making under LTCI, I consider a case in which recipients make a static decision about LTC utilization with given insurance coverage. Insurance coverage is expressed as a nonlinear budget set because a discount for LTC services is available only within the coverage region. I suppose that two insurance plans exist, with normal coverage (blue line) and generous coverage (red line). Although recipients enjoy a discounted out-of-pocket price (“oop price”) for LTC services within their coverage, they are obligated to pay the full price otherwise. Based on moral hazard, changes in coverage generosity (coverage limit) affect the demand of recipient H, but the demand of recipient L is unaffected. Consequently, the traditional concept of moral hazard predicts that these low-demand recipients who do not exhaust insurance coverage are unaffected by coverage changes because it does not change any economic factor for them, including price.

In contrast to the prediction of moral hazard discussed above, some behavioral economics concepts suggest that individuals who do not face effective price changes (recipient L in Figure 2) might still respond to changes in insurance coverage. The key empirical question of this study is whether an expansion (reduction) of insurance coverage increases (decreases) recipients’ demand through behavioral biases in decision-making. Many empirical studies of behavioral biases have demonstrated that various factors that are irrelevant to a rational decision-making framework frequently influence an individual’s decision. Although not excluding other possibilities, this study focuses on the following well-established behavioral biases: anchoring and heuristic thinking. Other potential explanations are discussed in section 6.

By the anchoring effect, inherently irrelevant information such as unrelated random numbers influences a person’s decision (Tversky and Kahneman, 1974). The psychological anchor is regarded as implicitly providing “suggestion” for its taker. In this way, the coverage limit of LTCI

Figure 2: Response to Insurance Coverage based on Moral Hazard



Notes: This figure presents a recipient's response to changes in insurance coverage based on moral hazard. Blue and red lines are budget constraints with different coverage regions. Individual H alters a recipient's demand for LTC (z_h and z'_h) according to a switch of coverage generosity. In contrast, Individual L does not respond to the change in coverage because she faces no change in economic environments including price. Consequently, based on standard theory, individuals whose LTC utilization is sufficiently lower than coverage limit should not respond to changes in insurance coverage.

may serve as a salient "starting point," or anchor, which frames a person's thinking about their demand for long term care services. It might also give an official "stamp of approval" (Bernheim, Fradkin, and Popov, 2015) to use services to the extent the coverage limit allows. The concept of heuristic thinking suggests that people often use a shortcut to make a decision quickly rather than considering details of the problem carefully. With LTCI, recipients might use a heuristic (such as a percentage of given coverage limit) for determining their demand for LTC rather than making it perfectly fit their own needs. Their LTC utilization might be influenced by changes in insurance coverage even when they do not face effective price changes if the decision-making of recipients is driven by these psychological biases. Importantly, both concepts predict that greater coverage change results in greater changes in utilization.

This study does not attempt to identify a specific behavioral mechanism underlying the relation between insurance coverage and LTC utilization but instead interprets any evidence of behavioral biases as being attributable to one or more psychological factors.

3 Data

LTCI Administrative Data

I use two sets of LTCI administrative data obtained from a local metropolitan government near Tokyo. The first set is LTCI claims data, which include monthly information related to eligibility, LTC utilization, and demographic characteristics for all LTCI recipients in the city. The available sample period of these data extends from June 2012 through March 2018. Eligibility information includes the care-needs level, start and end dates of each certification term, coinsurance rate, and public subsidy eligibility. For service utilization, claims data provides information related to how much each recipient uses and spends on a monthly basis for each type of LTC service. For this study, home-based care is grouped into five categories: home care, day care, home-visit nursing care, rehabilitation, and others. The claims data include limited information related to the demographic characteristics of recipients, providing age and gender but no information related to income and family structure.

The second dataset is newly available LTCI administrative data on care-needs certification. The most important information in this dataset is the assessed standardized care time, which is used for assigning recipients to a care-needs level. These data, which are available for each certification term, include a breakdown of how the final standardized care time was calculated (that is, it provides a hypothetical care time for each category of assistance) as well as other information related to care-needs certification such as the start and end dates of each certification term. The sample period of LTCI certification data is the same as LTCI claims data.

The analysis sample was created by linking the LTCI certification data and claims data via a unique ID number. This dataset allows association of recipients' LTC utilization and their standardized care time. From this preliminary dataset, recipients of several types were excluded from the baseline analysis sample. First, I omit nursing home resident recipients because the coverage limit is applied only to home-based care users. Second, recipients receiving public subsidies for LTCI are omitted because they face a different incentive scheme than usual recipients. The remaining recipients constitute the baseline sample.

Summary Statistics

Table 3 presents summary statistics for the baseline sample and the respective care-needs levels. Panel A shows demographic information of LTCI recipients.[15] The age of the baseline sample is around 81.2 years old, with recipients in high care-needs levels tending to be slightly older than those in low care-needs levels. For all care-needs levels, more than half of the recipients are women. Approximately 13% of recipients face a higher coinsurance rate (20%) because of high income. This rate is uniform across different care-needs levels. Change of care-needs level represents a fraction of recipients whose care-needs level is changed according to an assessment of the Certification Committee. In the baseline sample, only 5% of all recipients receive different coverage limits from those which the standardized care time indicates: the standardized care time determines the coverage limit in most cases.

Panel B shows the information related to the standardized care time calculated during care-needs certification and a breakdown of the hypothetical care time for each assistance category. With higher care-needs levels, assistance burdens related to eating, transferring, toileting and hygiene increase sharply, but other assistance categories are roughly constant across care-needs levels.

Panel C presents information related to LTC utilization. Day care is the most used LTC services, followed by home care. Home care and home-visit nursing care utilization monotonically increase as the care-needs level becomes higher. Demand for day care and rehabilitation decrease at higher care-needs levels. In the baseline sample, only 9% of recipients exceed the monthly coverage limit: the rate of exceeding the coverage limit is higher for recipients with high care-needs. Because most recipients use LTC services within their allocated coverage limit, this highlights the importance of investigating the behavior of recipients who do not entirely exhaust their insurance coverage.

Who Faces Price Changes?

To study behavioral biases associated with insurance coverage, one must ascertain who would face effective price changes because of coverage changes. Appendix Figure A2 shows the distribution of monthly LTC utilization for each care-needs level. The vertical red line indicates the coverage

[15] Because some recipients were allocated into different care-needs levels for several care-needs certifications, the sum of recipients for each care-needs level is not equal to the number of total recipients in the first column.

Table 3: Summary Statistics

	Baseline sample	Support level		Care level				
		level 1	level 2	level 1	level 2	level 3	level 4	level 5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Demographics								
Age	81.2	81.4	81.4	81.7	81.5	82.1	82.2	82.0
Woman	0.60	0.67	0.70	0.61	0.60	0.58	0.59	0.59
20% coinsurance	0.13	0.11	0.10	0.12	0.11	0.11	0.10	0.09
Change of care-needs level	0.05	0.00	0.06	0.07	0.01	0.09	0.09	0.07
Obs. (Recipient)	49,248	9,204	10,294	20,121	16,395	11,858	10,026	6,412
B. Care-needs certification								
Standardized care time	55.7	27.1	35.8	39.3	55.6	77.7	97.9	123.5
Eating	7.5	3.5	3.5	5.2	6.7	8.4	11.5	28.5
Transferring	6.1	0.7	2.1	2.4	5.1	11.0	17.1	17.6
Toileting	7.0	0.3	1.7	1.8	6.0	14.3	21.1	22.5
Hygiene	8.9	2.2	5.8	6.3	9.8	13.6	16.7	18.2
Housework	6.8	4.6	5.5	7.2	7.9	8.2	8.4	6.1
Dementia	6.8	5.8	5.9	6.5	7.5	7.9	7.0	6.9
Exercise	6.3	6.0	6.7	5.7	6.4	5.8	6.7	7.6
Medical care	5.8	4.0	4.6	4.2	5.1	5.9	9.1	16.1
Obs. (Recipient $\times$ Term)	132,881	18,605	20,845	32,552	23,530	15,808	12,807	8,734
C. Long-term care utilization								
Total expenditure per month (JPY)	105,120	25,078	43,259	73,615	105,681	167,705	207,286	262,789
Total unit per month	10,657	2,345	4,068	7,443	10,803	17,165	21,191	26,977
Home care	2,738	714	881	1,647	2,301	3,694	6,037	10,393
Day care	3,927	920	1,660	3,273	4,050	6,967	7,084	6,731
Home-visit nursing care	639	60	177	396	598	769	1,331	2,763
Rehabilitation	1,032	212	638	1,079	1,410	1,399	1,381	918
Exceed coverage limit	0.09	0.05	0.03	0.05	0.11	0.14	0.18	0.24
Monthly coverage limit (unit)		5,003	10,473	16,692	19,616	26,931	30,806	36,065
Obs. (Recipient $\times$ Month)	1,313,343	163,854	187,264	335,340	261,823	166,438	119,183	79,441

Notes: This table presents summary statistics for LTCI recipients analyzed for this study: recipients who use LTC services between June 2012 and March 2018. The first column shows statistics for all recipients irrespective of care-needs levels. The other columns present statistics for recipients who belong to specific care-needs levels separately. Recipients can be categorized into different care-needs levels for several care-needs certifications. Hence, the sum of recipients of each care-needs level is not equal to the number of total recipients (first column).

limit for each level. A clear "bunching" exists around the coverage limit in the distribution of Care levels 1-5, which suggests that recipients recognize given coverage limits and try to avoid paying higher prices outside the coverage. Because the bunching has some width, the coverage limit appears to restrict the demand of recipients whose utilization level is sufficiently close to it. One possible reason for recipients not completely exhausting their insurance coverage is that they might be saving some of their coverage for some unexpected LTC expenditure. Although an unexpected expenditure for LTC is rare and small compared with that for medical care, this precautionary motive might prevent recipients from exhausting insurance coverage.[16] Another possibility is that demand for LTC services is discrete rather than continuous in practice, which prevents recipients from fully exhausting their coverage limit. If this is the case, then the LTC utilization of recipients who do not completely exhaust their insurance might also be constrained by the coverage limit. These recipients would face effective price changes when coverage expands.

To address this concern, I set conservative criteria by which recipients whose monthly utilization is lower than 50% of the coverage limit are unaffected by price changes because of coverage expansion. I also adopt criteria assuming that recipients whose monthly utilization is higher than 80% of the coverage limit are affected by price changes. Similarly, recipients whose monthly utilization is lower than 80% of the one-stage lower coverage limit are assumed to be unaffected by price changes when they face a one-stage reduction in coverage.[17] I set 80% rather than 50% to ensure statistical power for analyzing behavioral biases related to coverage reduction.[18] Recipients whose monthly utilization is higher than 80% of the one-stage lower coverage limit would be affected by price changes. The following section describes the empirical strategy for estimating the effect of insurance coverage through behavioral biases, using those recipients unaffected by price changes.

4 Empirical Strategy

4.1 Overall Effects of Insurance Coverage

The empirical strategy used throughout this study is based on an RD design. As described in this section, a simple RD design is used for estimation of overall effects of insurance coverage on LTC utilization, which includes both responses to price changes ("price effects") and behavioral biases associated with insurance coverage ("behavioral effects"). Section 4.2 then describes how coverage changes are used to isolate behavioral effects.

First, to estimate recipients' responses to various degrees of insurance coverage generosity, I implement an RD design exploiting thresholds of the standardized care time that generates discon-

[16]For example, family members of the recipient must leave home urgently for a couple of days, and the recipient uses additional short-stay services.

[17]For example, one-stage lower coverage of Care level 3 is Care level 2.

[18]Recipients' needs for LTC tend to increase as they age. Therefore, there are small number of recipients whose care-needs level is changed to lower levels.

tinuous changes in the monthly coverage limits. Figure 3 presents the relation between standardized care time and coverage limits. Five thresholds exist at 32, 50, 70, 90, and 110 min; these thresholds respectively change the coverage limit by 5,470 (+109.3%), 2,924 (+17.5%), 7,315 (+37.3%), 3,875 (+14.4%), and 5,259 (+17.1%) units. The relation between standardized care time and coverage limit is not deterministic because the recipients' care-needs level might be altered by the Certification Committee. Consequently, I exploit these thresholds as instruments for the generosity of insurance coverage.

Given a particular threshold, I only use recipients whose standardized care time is in one of the two neighboring care-needs levels separated by the threshold. The effect of insurance coverage on LTC utilization at each of the five different thresholds is expressed as:

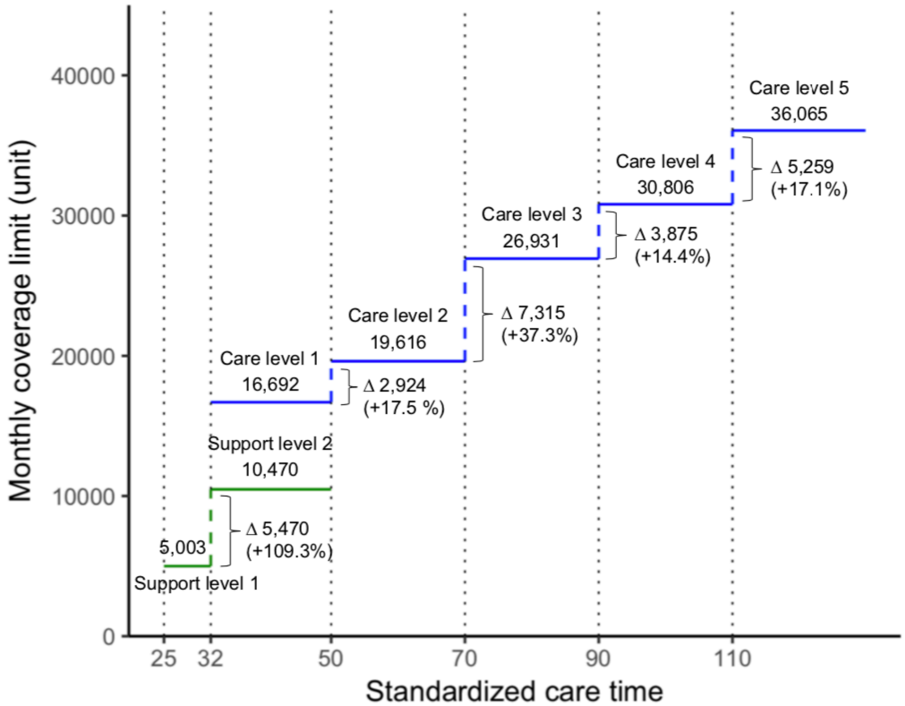
$$Utilization_{it} = \alpha^c + \beta^c Coverage_{it} + f^c(Caretime_{it}) + X_{it}\gamma^c + \varepsilon_{it}, \tag{1}$$

where $Utilization_{it}$ stands for the LTC utilization of recipient i in year-month t measured by monthly total units.[19] $Coverage_{it}$ denotes the generosity of insurance coverage (coverage limit). $Caretime_{it}$ expresses a standardized care time, which is a running variable. The covariates in X_{it} include age, gender, coinsurance rate, and the hypothetical care times of each category of assistance, which are used collectively to calculate standardized care time. Also, $f^c(\cdot)$ signifies a set of functions of standardized care time specified below. The parameter of interest is β^c, denoting the effect of a one-unit increase in insurance coverage on LTC utilization.[20] All parameters are

[19] An adjustment must be made to reflect service utilization accurately because the number of units of day care service might be higher at upper care-needs levels because of the higher price of these services. To address this point, day care service units are normalized using a price of Care level 1 as a baseline. Hereinafter, the measure of LTC utilization refers to these adjusted data. Effects of day care price changes on LTC utilization are assumed to be negligible because price changes across care-needs levels are fairly small (approx. 10%).

[20] For the 32 and 50 min thresholds, ambiguity in the sorting procedure of recipients into either Support level 2 or Care level 1 might present a challenge in the interpretation of the estimated responses to insurance coverage. If standardized care time is between 32 and 50 min, then healthy recipients are allocated to Support level 2 whereas unhealthy recipients are assigned to Care level 1. In the estimation for the threshold at 32 min, the demand of Support level 1 is compared with that of Support level 2 around the threshold. Therefore, recipients just above the threshold might not be comparable to those just below the threshold because the recipients just above the threshold might be "overly healthy" as a result of the sorting procedure. The summary statistics show that healthy recipients tend to require less LTC than unhealthy recipients do. Therefore, the estimated responses might be biased downward at the 32 min threshold. Similarly, recipients just below the threshold at 50 min might be "overly unhealthy" compared with those just above the threshold. For that reason, those estimates might be biased downward. However, in both cases, this would cause the estimates to be conservative. The main implication of the analysis is unaffected by this sorting procedure.

Figure 3: Standardized Care Time and Monthly Coverage Limit



Notes: This figure presents the relation between standardized care time and monthly coverage limit. The green line represents the coverage limits for the Support level; the blue line represents those for the Care level.

indexed by a threshold c because they are estimated for each threshold.

The first-stage regression is

$$Coverage_{it} = \alpha_0^c + \beta_0^c \mathbb{1}\{Caretime_{it} \geq Cutoff\} + f_0^c(Caretime_{it}) + X_{it}\gamma_0^c + \varepsilon_{it}, \tag{2}$$

where $Cutoff$ denotes one cutoff values of standardized care time which separates neighboring care-needs level; that is, $Cutoff \in \{32, 50, 70, 90, 110\}$ depending on the threshold exploited for estimation. A dummy variable, $\mathbb{1}\{Caretime_{it} \geq Cutoff\}$, takes a value 1 if standardized care time is greater than or equal to a given cutoff value. Also, $f_0^c(\cdot)$ (and $f^c(\cdot)$ in equation 1) is a set of functions of a running variable: its parameters are free to vary on either side of a given threshold. The function is specified as a linear, quadratic, or cubic function for parametric estimation.[21] A nonparametric local polynomial regression with robust confidence intervals proposed by Calonico,

[21] Both sides of the threshold use the same parametric specification.

Cattaneo, and Titiunik (2014) is also estimated. Standard errors are clustered at the recipient level in equation 1 and 2.

4.2 Coverage Changes and Identification of Behavioral Effects

The limitation of the RD design above is that it cannot disentangle whether the overall effects of insurance coverage result from behavioral effects or price effects. To examine the existence of behavioral effects, one must see whether recipients who do not exhaust insurance coverage respond to coverage changes, as described in section 2 (see Figure 2).

To identify behavioral effects, I make use of coverage changes (including both an expansion and a reduction in coverage) caused by reclassification of recipients' care-needs levels. Specifically, I use a two-step procedure to narrow down the recipients and then implement the RD design. First, I focus on recipients whose average monthly utilization during any certification term s is less than 50% of the coverage limit. As discussed in section 3, this step excludes recipients who exhaust the coverage limit and who might therefore be influenced by price effects caused by changes in insurance coverage. Recipients using services amounting to less than 50% of the coverage limit are defined as "low-demand," whereas those whose service utilization is higher than 80% are "high-demand." I assume that low-demand recipients are affected by behavioral effects of coverage changes, but not by price effects.

In the second step, low-demand recipients are narrowed down further to those whose standardized care time for the next term $s+1$ is in either the same or one stage higher care-needs level compared with that of term s. Recipients who are switched to an upper care-needs level and who are more likely to face a higher coverage limit can be considered a "treatment group," whereas those who remain in the same care-needs level can be regarded as a "control group." The key to the identification strategy is that, near the threshold, it is likely to be random whether low-demand recipients will be in the treatment group or in the control group: Among recipients who had the same standardized care time in the previous term, some recipients face coverage expansion with their new standardized care time slightly exceeding the threshold, whereas other recipients face the same coverage by slightly *not* exceeding the threshold. With the selected low-demand recipients, the RD design can be implemented to estimate the behavioral effects of coverage expansion (increase in coverage limit) on LTC utilization.

Using low-demand recipients selected through the procedure described above, behavioral effects of coverage expansion are estimated through leveraging each of the five thresholds separately as in the previous RD design. The causal relation of interest can be written as:

$$\begin{aligned}\Delta Utilization_{it}^{s,s+1} = \alpha^c + \beta^c \Delta Coverage_i^{s,s+1} &+ f^c(Caretime_{is+1}) \\ &+ \gamma^c Caretime_{is} + X_{it}\eta^c + \varepsilon_{it},\end{aligned} \tag{3}$$

where $\Delta Utilization_{it}^{s,s+1}$ represents a change in the LTC utilization of recipient i, which is calculated as a difference between the monthly utilization at year-month t during term $s+1$ and mean monthly utilization during the previous term s (before reclassification). $\Delta Coverage_i^{s,s+1}$ is a change in insurance coverage between s and $s+1$ recipient i faces. β^c is the target parameter indicating behavioral effects of one-unit coverage expansion on LTC utilization.

The first-stage regression is

$$\begin{aligned}\Delta Coverage_i^{s,s+1} = \alpha_0^c + \beta_0^c \mathbb{1}\{Caretime_{is+1} \geq Cutoff\} &+ f_0^c(Caretime_{is+1}) \\ &+ \gamma_0^c Caretime_{is} + X_{it}\eta_0^c + \varepsilon_{it}.\end{aligned} \tag{4}$$

In this model, standardized care time during $s+1$, $Caretime_{is+1}$, is a running variable because all low-demand recipients subject to a specific estimation have the same coverage limit during term s, so the coverage change faced by each recipient depends on their standardized care time during $s+1$. The functional specification of $f_0^c(\cdot)$ (and $f^c(\cdot)$) is the same as that for the earlier model. I control the standardized care time during prior term s, $Caretime_{is}$, to compare recipients who also have similar past health conditions. Covariates in X_{it} include age, gender, coinsurance rate, and the hypothetical care times of each category of assistance.

Similarly, by conditioning on high-demand rather than low-demand recipients, I estimate the effects of coverage expansion on recipients who have exhausted insurance coverage using the same strategy. High-demand recipients might be affected by both behavioral and price effects. It is not possible to disentangle these effects among these recipients. Therefore, the effects on high-demand recipients must be interpreted as a combination of these two effects.

Another benefit of exploiting coverage changes is that it also allows estimation of coverage reduction (decrease in coverage limit) effects. In this case, I focus on recipients whose standardized care time in the following term $s+1$ is in the same or one stage lower care-needs level compared with that of term s. Estimation of coverage reduction closely resembles the case of coverage expansion. I describe the procedure in Appendix B.

Why Not a Difference-in-Differences?

Another approach to estimating behavioral effects is to exploit an exogenous timing of coverage changes. The timing of next care-needs certification is predetermined and most recipients follow the schedule. I can regard low-demand recipients who face coverage changes at a given timing as a treatment group and those who do not take the care-needs certification at the same time as a control group and estimate the behavioral effects using a difference-in-differences (DID) approach.

The DID approach, however, presents a severe difficulty in identifying behavioral effects in this context. Recipients tend to change monthly plans for LTC utilization at the timing of care-needs certification even if their insurance coverage does not change. This tendency prevails probably because it is a good opportunity for recipients to rethink their monthly utilization plan. Therefore, changes in the utilization at the timing of coverage changes might occur not only because of coverage changes but also because of renewed care-needs certification per se. This means that exogenous variation of the timing of care-needs certification cannot be used to identify the effect of coverage changes, needless to say, behavioral effects. In contrast, the above RD design specifically examines recipients after a renewed care-needs certification, which offsets its effect on LTC utilization and which identifies behavioral effects of coverage changes.

4.3 Estimation of the Health Consequences of Long-Term Care

Using more home-based LTC can be either a positive or negative influence on recipients' health. Home care can reduce the risk of household accidents involving recipients. In addition, day care encourages recipients to take exercise and to communicate with other people. These activities might help to improve their health as well. However, it is also possible that healthy recipients who rely too heavily on home care for their daily activities might eventually lose the ability to manage activities that they once were able to do. It remains unclear whether positive or negative effects dominate. Preventing deterioration of recipients' health is beneficial both for the recipients' quality of life and for reducing the public cost of LTCI. Therefore, the health consequences of LTC is an important empirical question.

Using recipients' responses to insurance coverage, I estimate the effect of LTC utilization on their health outcomes through 2SLS estimation. Recipients in the Support level can only use preventive LTC whereas those in the Care level use usual LTC services. The causal relation of interest can be expressed as shown below.

$$Health_{is+1} = \alpha^c + \beta^c Utilization_{is} + f^c(Caretime_{is}) + X_{is,s+1}\gamma^c + \varepsilon_{is}. \tag{5}$$

In this estimation, $Health_{is+1}$ expresses a measure of the health status of recipient i at term $s+1$. I use three variables as recipient health measures: (i) standardized care time calculated at the beginning of term $s+1$, (ii) LTC utilization during term $s+1$, and (iii) whether recipients end up entering a nursing home during $s+1$. $Utilization_{is}$ in equation 5 stands for the mean monthly LTC utilization of recipient i during term s. $f^c(\cdot)$ denotes a function of the standardized care time. $X_{is,s+1}$ includes the length of time of term s as well as the recipient's characteristics including the hypothetical care time of each category of assistance, as in the regressions discussed above. If utilization information is used as outcomes, standardized care time at $s+1$ is included in $X_{is,s+1}$ because LTC utilization is affected by insurance coverage (care-needs level). The parameter of interest is β^c, which stands for the health effects of LTC utilization.

Long-term care utilization is an endogenous variable. Therefore, I use each threshold generating discontinuous variation in coverage limit as an instrument for it. The first-stage of 2SLS is estimated by the following regression at each of the five thresholds.

$$Utilization_{is} = \alpha_0^c + \beta_0^c \mathbb{1}\{Caretime_{is} \geq Cutoff\} + f_0^c(Caretime_{is}) + X_{is,s+1}\gamma_0^c + \varepsilon_{is}. \tag{6}$$

The notations are the same as those used for the previous regressions; $\mathbb{1}\{Caretime_{is} \geq Cutoff\}$ is an instrument for LTC utilization. The functional specification of $f_0^c(\cdot)$ in the first-stage is same as $f^c(\cdot)$ in the second-stage.

It is noteworthy that the estimates represent the short-run health effects of LTC utilization. The 2SLS estimation above uses LTC utilization only during the first term, $s=1$, to examine direct effect of LTC utilization specifically rather than the cumulative effect from past utilization.[22] The

[22]Distinguishing whether responses to insurance coverage result from behavioral effects or price effects in this

average length of the first term is 6.8 months. Therefore, the estimated health effect is of different LTC utilization for half a year.

4.4 Validity Tests for the RD Design

Distribution of the Running Variable and McCrary Test

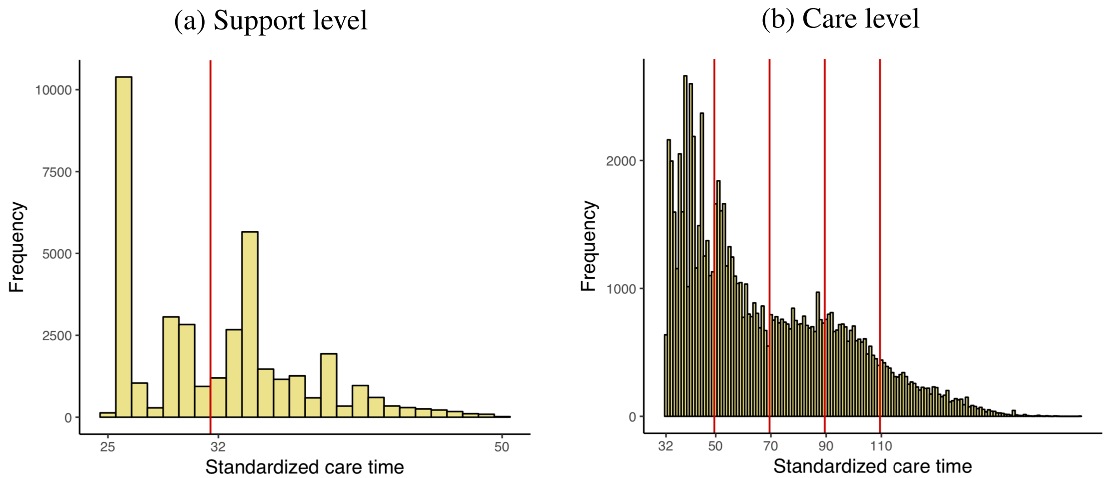
This section describes validation of local randomness around thresholds. First, I examine the smoothness of the distribution of the running variable around thresholds. Figure 4 presents the distribution of standardized care time for the baseline sample. Panel (a) of Figure 4 portrays the distribution for the Support level, which appears fairly smooth around the thresholds. Panel (b) shows the distribution for the Care level. Although a noticeable jump is apparent just above the thresholds of 50 min, it is smooth around other thresholds. Appendix Figure A3 shows the distribution for recipients who take their first care-needs certification and who are used to estimate health effects of LTC utilization. The distribution resembles Figure 4: smooth except the threshold of 50 min. Figure 5 depicts the distribution after reclassification conditioning on low-demand recipients who are used to identify behavioral effects of coverage expansion. Compared with Figure 4, no distributions have any visible discontinuity around the thresholds. This validation test suggests strongly that local randomness is satisfied in the case of coverage expansion.

In contrast, the local randomness assumption appears to be violated in the case of coverage reduction. Appendix Figure A4 presents the distribution of the running variable, conditional upon the low-demand recipients who are used to identify behavioral effects of coverage reduction. The figures clearly present discontinuities at all thresholds, suggesting that care-needs certification examiners avoid reducing recipients' insurance coverage, and also suggesting that the assignment of recipients to either side of the threshold might not be random.

To test the smoothness of the distribution statistically, I apply the local polynomial density test proposed by Cattaneo, Jansson, and Ma (2020) at each threshold. Panel A and B in Appendix Table A1 respectively present estimates of the test with all recipients in the baseline sample and those who take the first care-needs certification. Panel C presents estimates of the same test with coverage expansion, which is estimated separately for low-demand, high-demand, and all recipi-

estimation is impossible because I use LTC utilization of the first term and cannot condition on the utilization during the prior term.

Figure 4: Distribution of Standardized Care Time (All Recipients)



Notes: This figure presents the distribution of standardized care time for Support level (Panel (a)) and Care level (Panel (b)). The distribution is constructed using all recipients in the baseline sample. The bin width is 1 min of standardized care time.

ents. Panel D presents results for coverage reduction. Most importantly, with only one exception, the discontinuity of the distribution is not detected in the case of coverage expansion. As Appendix Figure A4 suggests, however, the discontinuity is statistically significant in the case of coverage reduction.

Covariates Balance Test

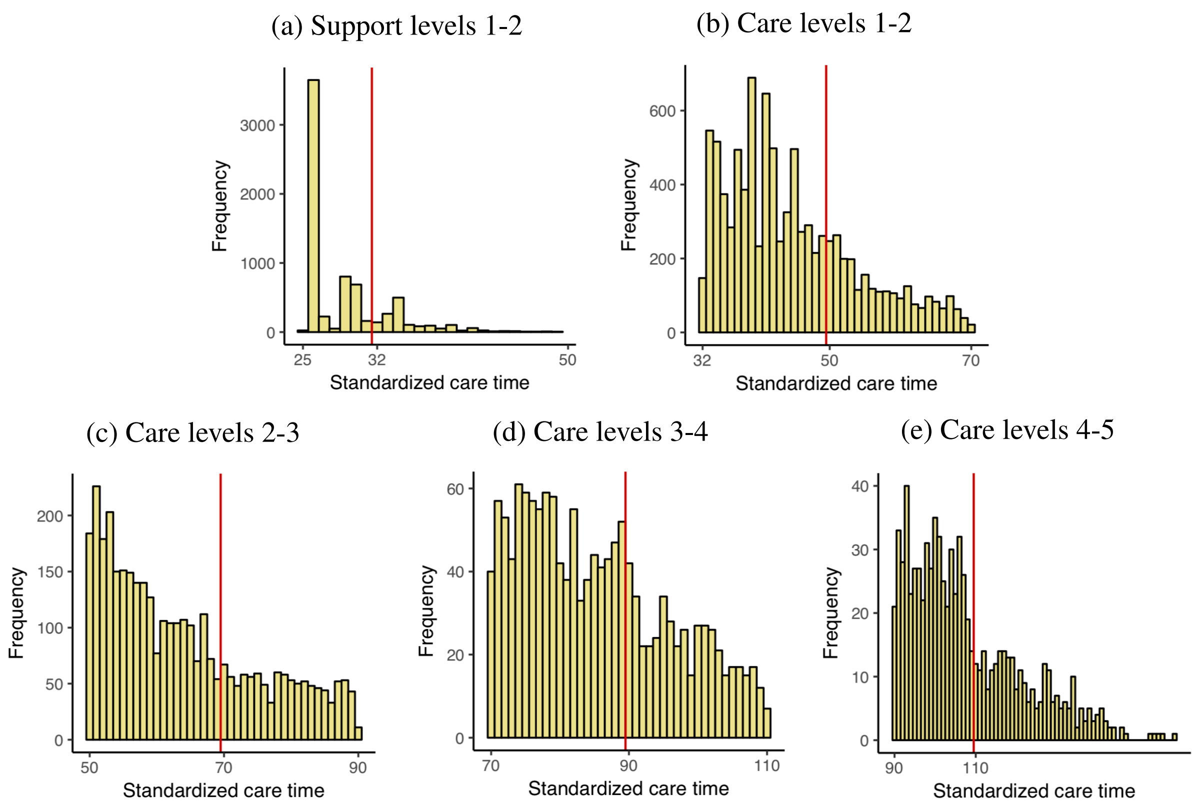
Furthermore, I examine whether predetermined recipient characteristics are balanced around the thresholds. For this analysis, the following parametric equation is estimated as

$$Y_{is} = \alpha^c + \beta^c \mathbb{1}\{Caretime_{is} \geq Cutoff\} + f^c(Caretime_{is}) + \varepsilon_{is}, \tag{7}$$

where Y_{is} is the covariate of recipient i during certification term s. Linear and quadratic specifications are used for $f^c(\cdot)$.

Table 4 presents estimates for β^c with recipients used for the estimation, which exploits a coverage expansion. The results are presented separately for low-demand, high-demand, and all recipients. With a few exceptions, the estimates are not significant, which indicates that the local randomness assumption is reasonably satisfied. Appendix Table A2 presents β^c for all recipients

Figure 5: Distribution of Standardized Care Time (Coverage Expansion, Low-Demand)



Notes: This figure presents the distribution of standardized care time for each care-needs level. The distribution is constructed using the low-demand recipients after reclassification of care-needs levels (either the same or one-stage higher level). The bin width is 1 min of standardized care time.

in the baseline sample. Except for the quadratic specification for Support levels 1-2, the variations of covariates around thresholds are mostly not significant. Appendix Table A3 presents estimates for recipients who take the first care-needs certification. These estimates are also not significant in most cases. These results indicate that the covariates are well balanced around the respective thresholds. Appendix Table A4 presents estimates for the recipients used for analyzing the response to a coverage reduction. Despite the sharp discontinuity in the distribution of the running variable around thresholds, the covariates are balanced, which suggests that the discontinuity could be attributed to unobservable factors.

Overall, the validity test suggests that the RD identification assumption is reasonably satisfied for estimates of coverage expansion. Regarding coverage reduction, whereas observable characteristics are balanced around the thresholds, unobservable factors might be causing sharp discontinuities in the distribution of the running variable. Therefore, I regard estimates of coverage expansion

Table 4: Covariates Balance Tests (Coverage Expansion)

	All recipients				Low-demand recipients				High-demand recipients			
	Linear		Quadratic		Linear		Quadratic		Linear		Quadratic	
	Coeff. (1)	SE (2)	Coeff. (3)	SE (4)	Coeff. (5)	SE (6)	Coeff. (7)	SE (8)	Coeff. (9)	SE (10)	Coeff. (11)	SE (12)
Support levels 1-2												
Age	0.069	(0.330)	1.627***	(0.613)	-0.140	(0.383)	1.072	(0.712)	-0.814	(1.106)	-0.198	(1.741)
Female	0.000	(0.020)	-0.093**	(0.040)	0.006	(0.025)	-0.074	(0.049)	0.056	(0.069)	-0.159	(0.123)
20% coinsurance	-0.001	(0.011)	0.056**	(0.022)	-0.008	(0.015)	0.030	(0.028)	-0.020	(0.043)	0.172**	(0.075)
Observation	10,903				7,112				847			
Cluster	5,631				4,039				538			
Care levels 1-2												
Age	1.046***	(0.271)	1.530***	(0.397)	0.769**	(0.347)	1.381***	(0.505)	0.812	(0.833)	0.959	(1.254)
Female	-0.021	(0.016)	-0.002	(0.024)	-0.037*	(0.021)	0.001	(0.031)	-0.028	(0.045)	0.058	(0.067)
20% coinsurance	0.011	(0.009)	0.026*	(0.014)	0.004	(0.013)	0.016	(0.019)	0.018	(0.021)	0.063**	(0.032)
Observation	14,806				9,366				1,730			
Cluster	10,454				7,136				1,354			
Care levels 2-3												
Age	0.515	(0.434)	0.535	(0.666)	0.638	(0.726)	0.154	(1.079)	0.375	(0.778)	2.506**	(1.247)
Female	0.031	(0.024)	0.018	(0.036)	0.037	(0.038)	0.064	(0.058)	0.026	(0.043)	0.041	(0.066)
20% coinsurance	-0.024*	(0.012)	-0.044**	(0.020)	-0.052***	(0.020)	-0.014	(0.023)	-0.016	(0.026)	-0.039	(0.036)
Observation	8,240				3,586				2,310			
Cluster	6,439				2,934				1,920			
Care levels 3-4												
Age	-0.572	(0.541)	-0.803	(0.796)	2.687**	(1.044)	2.462	(1.508)	-1.707**	(0.732)	-1.964*	(1.087)
Female	0.019	(0.028)	-0.004	(0.040)	0.005	(0.055)	0.037	(0.078)	-0.006	(0.040)	-0.012	(0.057)
20% coinsurance	-0.005	(0.014)	-0.008	(0.020)	0.047	(0.030)	0.030	(0.040)	-0.036*	(0.020)	-0.037	(0.029)
Observation	4,813				1,445				2,075			
Cluster	3,867				1,217				1,725			
Care levels 4-5												
Age	-0.376	(0.659)	-0.026	(0.924)	-1.384	(1.580)	-1.254	(2.137)	-0.848	(0.869)	-0.042	(1.230)
Female	0.015	(0.032)	0.015	(0.047)	0.036	(0.068)	0.103	(0.102)	-0.021	(0.043)	-0.014	(0.063)
20% coinsurance	0.014	(0.016)	0.019	(0.024)	-0.010	(0.033)	-0.036	(0.054)	0 .038*	(0.021)	0.040	(0.028)
Observation	3,435				815				1,785			
Cluster	2,700				686				1,433			

Notes: This table presents estimates of covariate balance tests for the linear and quadratic RD specification from equation 7. These estimations use recipients who are used for analyzing coverage expansion after the reclassification of care-needs levels. Low-demand recipients are those whose average monthly LTC utilization during the earlier certification term is less than 50% of a given coverage limit. High-demand recipients are those whose average monthly LTC utilization during the previous certification term is higher than 80% of a given coverage limit. *** p<0.01, ** p<0.05, * p<0.10.

as reliable main results for behavioral effects. To address the potential violation of local randomness, a "donut hole" RD design is also implemented by excluding observations near the thresholds as a robustness check.

5 Results

5.1 Overall Effects of Insurance Coverage

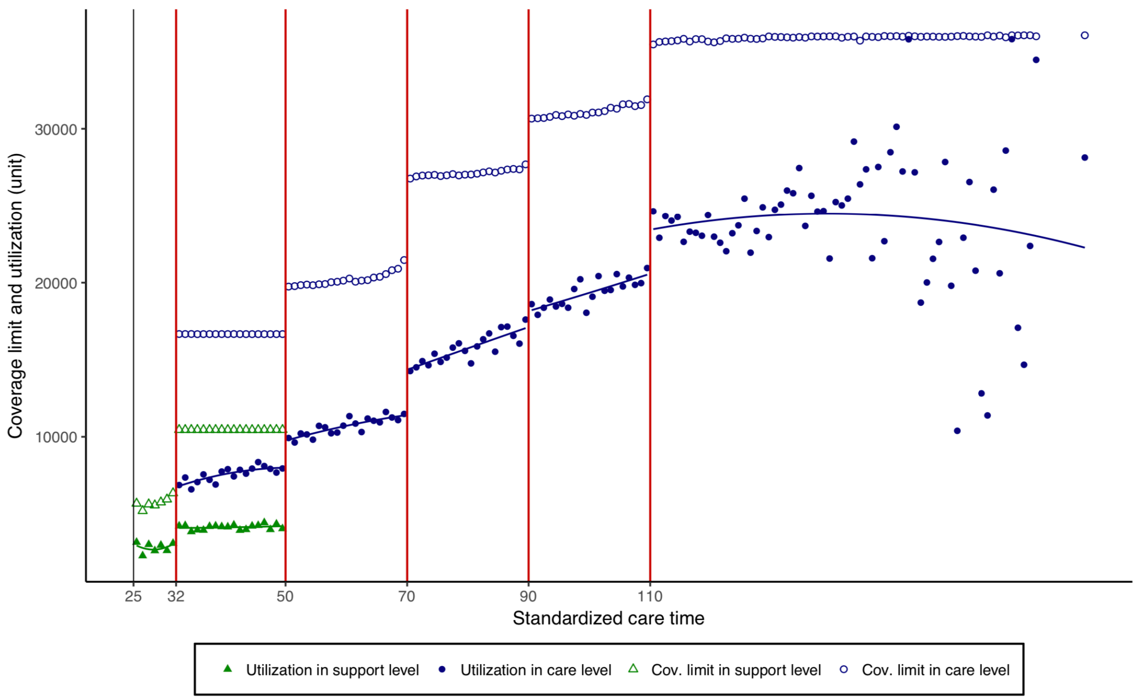
First of all, Figure 6 presents the relation between standardized care time, monthly coverage limits, and monthly LTC utilization using all baseline sample. Standardized care time is divided into 1-min-wide interval (bin); hollow circles and triangles respectively represent local average of coverage limits within bins for the Care level and the Support level. Each filled circles and triangles represent the local average of the monthly LTC utilization within a bin. A quadratic prediction is fitted on the plots for each care-needs level. It is noteworthy that coverage limits increase discontinuously at all thresholds, indicating that the thresholds are valid instruments for the insurance coverage generosity. Also, LTC utilization also increases at all thresholds. This strongly suggests that insurance coverage significantly affects LTC utilization through price and/or behavioral effects.

Table 5 presents the first-stage estimates (β_0 in equation 2) and the second-stage estimates (β in equation 1) for the overall effect of insurance coverage at each threshold. Each column presents results for a specific polynomial order and nonparametric estimates. The first-stage estimates are positive and significant at all thresholds, irrespective of specifications, which confirms the validity of instruments. The variation in first-stage estimates by threshold strongly reflects the "mechanical" relation between standardized care time and coverage limits, as portrayed in Figure 3.

The second-stage estimate represents effects of having more generous insurance coverage by one unit on LTC utilization. The estimates are positive and significant at almost all thresholds and specifications. These estimates show unambiguously that generous insurance coverage increases LTC utilization. Importantly, although only a small fraction of Support level recipients exhaust their insurance coverage, more generous insurance coverage leads to higher LTC utilization. This result suggests that behavioral biases play a major role in recipients' responses to changes in insurance coverage.

The estimates presented above demonstrate the existence of important heterogeneity among recipients with different health conditions. First, Support level recipients are less sensitive to insurance coverage than those of the Care level. One unit increase in the coverage limit for the Support level increases utilization by around 0.2 units, whereas that for the Care level increases utilization by 0.5-0.8 units. This difference might be attributable to the fact that few recipients

Figure 6: Coverage Limit and Long-Term Care Utilization



Notes: This figure presents the relation between coverage limit and LTC utilization using the baseline sample. I divide standardized care time into 1 min-wide interval (bins). Hollow circles and triangles respectively represent a local average of coverage limit for Care level and Support level. Each filled circle and triangle represents a local average of a monthly total unit of LTC utilization within bins and a quadratic prediction is fitted on the plots for each care-needs level.

in the Support level exhaust their insurance coverage, and most recipients are unaffected by price effects. Second, even among Care level recipients, the effect of insurance coverage tends to grow as the care-needs levels increase. The summary statistics show that recipients who belong to higher care-needs levels are more likely to exhaust their insurance coverage. Therefore, the trend supports the prediction that the price effect will increase as more recipients exhaust insurance coverage.

5.2 Behavioral Effects of Coverage Expansion

The estimation results in the preceding section suggest that behavioral biases might play a key role in recipients' responses to insurance coverage changes. The results also clarify the necessity of excluding price effects to identify behavioral biases, because the price effect strength significantly affects LTC utilization. In this section, the effects of coverage expansion on LTC utilization are estimated for recipients of three types: low-demand, high-demand, and all recipients. As explained

Table 5: Overall Effects of Insurance Coverage

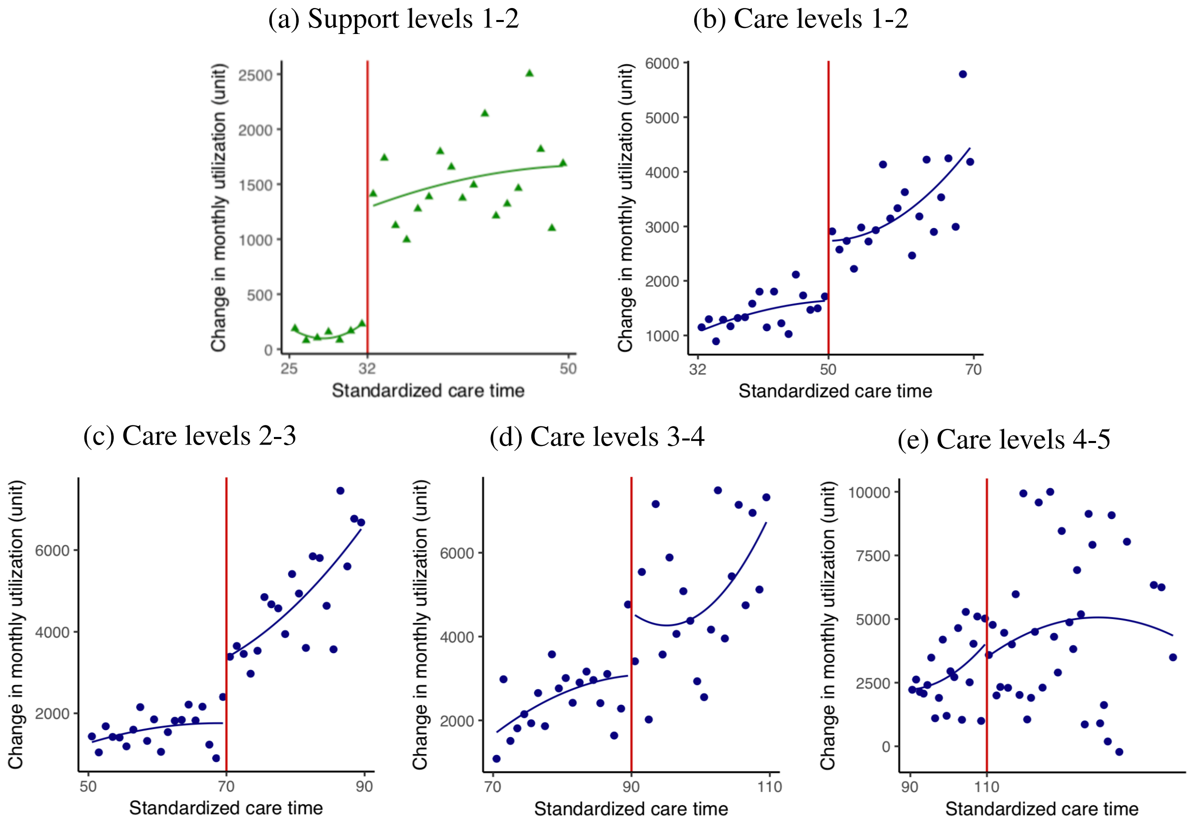
	Linear		Quadratic		Cubic		LPR			
	Coeff. (1)	SE (2)	Coeff. (3)	SE (4)	Coeff. (5)	SE (6)	Coeff. (7)	SE (8)	Obs. (9)	Cluster (10)
Support levels 1-2										
First-Stage	4,183.6***	(49.9)	3,859.1***	(107.2)	3,491.7***	(196.7)	3,291.5***	(218.5)	339,271	15,646
Second-Stage	0.260***	(0.014)	0.290***	(0.027)	0.176***	(0.049)	0.122**	(0.058)		
Care levels 1-2										
First-Stage	2,957.7***	(22.5)	3,135.6***	(28.8)	2,990.2***	(34.3)	3,038.4***	(38.7)	549,574	28,607
Second-Stage	0.550***	(0.043)	0.524***	(0.057)	0.566***	(0.080)	0.614***	(0.109)		
Care levels 2-3										
First-Stage	5,947.5***	(54.7)	5,729.2***	(92.8)	5,360.7***	(133.7)	5,193.8***	(161.7)	398,238	22,848
Second-Stage	0.459***	(0.037)	0.533***	(0.056)	0.477***	(0.082)	0.447***	(0.094)		
Care levels 3-4										
First-Stage	3,101.0***	(39.5)	3,080.6***	(56.8)	2,965.0***	(75.4)	2,856.6***	(104.1)	274,045	18,801
Second-Stage	0.522***	(0.097)	0.455***	(0.141)	0.542***	(0.189)	0.427	(0.263)		
Care levels 4-5										
First-Stage	3,942.4***	(57.5)	3,687.9***	(87.3)	3,630.3***	(120.2)	3,619.0***	(123.2)	189,281	14,371
Second-Stage	0.607***	(0.108)	0.726***	(0.156)	1.051***	(0.207)	1.003***	(0.224)		

Notes: This table presents the first-stage estimates of β_0^c in equation 2 and the second-stage estimates of β^c in equation 1. The first to sixth columns show estimates for different specifications of $f_0(Caretime_{it})$ and $f(Caretime_{it})$: linear, quadratic, and cubic, respectively. The seventh and eighth columns shows the nonparametric local polynomial regression (LPR) estimates using the robust confidence intervals proposed by Calonico, Cattaneo, and Titiunik (2014). *** p<0.01, ** p<0.05, * p<0.10.

in earlier section, the main outcome variable is monthly LTC utilization.

Figure 7 shows utilization changes for low-demand recipients to assess whether coverage expansion affects LTC utilization through behavioral biases. As shown in section 4.2, the estimation for each threshold uses a different set of recipients. Therefore, the plots around each threshold are presented in separate panels. Recipients to the right of the threshold are much more likely to face coverage expansion. This figure presents significant behavioral effects and their notable heterogeneity among recipients with different health status. Panels (a)-(c) in the figure illustrate that the utilization of low-demand recipients responds to coverage expansion. The salience of this response suggests strongly that low-demand recipients with less-severe health conditions are affected by behavioral effects. In contrast, Panels (d) and (e) show that low-demand recipients with severe health conditions exhibit little or no visible behavioral biases associated with insurance coverage. Appendix Figure A5 shows plots of changes in utilization for high-demand recipients. The plots

Figure 7: Changes in Long-Term Care Utilization (Coverage Expansion, Low-Demand)



Notes: This figure presents effects of expanding insurance coverage on LTC utilization using low-demand recipients who end up being either the same or one stage worse after the reclassification. I divide standardized care time into 1 min-wide interval (bins). Each plot represents a local average of changes in monthly LTC utilization before and after reclassification. I plot the local average for both the Support level (Panel (a)) and the Care level (Panels (b)-(e)) and a quadratic prediction is fitted on plots for each care-needs level.

tend to be sparse because of the small sample size, but LTC utilization by high-demand recipients is affected markedly by coverage expansion. These responses are consistent with the prediction of the moral hazard. Appendix Figure A6 shows plots incorporating all recipients irrespective of prior utilization: coverage expansion increases LTC utilization at all thresholds, reflecting both behavioral and price effects.

Table 6 presents estimates of the effect of one-unit coverage expansion on LTC utilization. For each threshold, estimates of low-demand recipients and those of high-demand recipients are presented separately. The first to eighth columns show the estimates and standard errors of each specific polynomial order and nonparametric estimates. The first-stage estimates for coverage expansion are given in Appendix Table A5, which presents the validity of instruments. As in the

Table 6: Effects of Coverage Expansion on Long-Term Care Utilization

	Linear		Quadratic		Cubic		LPR			
	Coeff. (1)	SE (2)	Coeff. (3)	SE (4)	Coeff. (5)	SE (6)	Coeff. (7)	SE (8)	Obs. (9)	Cluster (10)
<u>Support levels 1-2</u>										
All recipients	0.235***	(0.013)	0.242***	(0.021)	0.289***	(0.031)	0.221***	(0.062)	110,120	5,631
Low-demand	0.202***	(0.014)	0.205***	(0.023)	0.237***	(0.035)	0.171***	(0.057)	71,747	4,039
High-demand	0.528***	(0.060)	0.574***	(0.087)	0.678***	(0.122)	0.732**	(0.300)	8,548	538
<u>Care levels 1-2</u>										
All recipients	0.321***	(0.046)	0.345***	(0.065)	0.328***	(0.083)	0.339***	(0.106)	192,276	10,454
Low-demand	0.252***	(0.056)	0.328***	(0.079)	0.316***	(0.102)	0.407***	(0.125)	121,190	7,136
High-demand	0.682***	(0.182)	0.596**	(0.263)	0.413	(0.321)	0.247	(0.397)	22,236	1,354
<u>Care levels 2-3</u>										
All recipients	0.250***	(0.036)	0.211***	(0.054)	0.237***	(0.075)	0.307***	(0.093)	110,245	6,439
Low-demand	0.184***	(0.054)	0.260***	(0.080)	0.241**	(0.110)	0.273**	(0.138)	55,524	3,231
High-demand	0.323***	(0.079)	0.186	(0.121)	0.319*	(0.176)	0.370	(0.230)	28,225	1,920
<u>Care levels 3-4</u>										
All recipients	0.504***	(0.106)	0.517***	(0.147)	0.494*	(0.190)	0.198	(0.241)	63,109	3,867
Low-demand	0.230	(0.196)	0.453	(0.279)	0.218	(0.363)	-0.460	(0.470)	20,085	1,217
High-demand	0.700***	(0.161)	0.561***	(0.216)	0.488*	(0.279)	0.281	(0.269)	25,902	1,725
<u>Care levels 4-5</u>										
All recipients	0.170*	(0.098)	0.223	(0.152)	0.297	(0.208)	0.441*	(0.266)	43,881	2,700
Low-demand	0.005	(0.235)	-0.377	(0.369)	-0.617	(0.495)	-0.659	(0.665)	10,760	686
High-demand	0.355***	(0.129)	0.487**	(0.202)	0.609**	(0.282)	0.690**	(0.308)	22,016	1,433

Notes: This table presents second-stage estimates of β^c in equation 3. The first to sixth columns present the estimates for different specifications of $f(Caretime_{it})$: linear, quadratic, and cubic. The seventh and eighth columns show the nonparametric local polynomial regression (LPR) estimates using the robust confidence intervals proposed by Calonico, Cattaneo, and Titiunik (2014). Low-demand recipients are those for which average monthly LTC utilization during the previous certification term was less than 50% of a given coverage limit. High-demand recipients are those for which the average monthly LTC utilization during the prior certification term was more than 80% of a given coverage limit. *** p<0.01, ** p<0.05, * p<0.10.

earlier estimation, variation in first-stage estimates by threshold strongly reflects the mechanical relation between standardized care time and coverage limits.

The estimation results shed light on some important aspects of behavioral biases associated with coverage expansion. First, coverage expansion significantly increases LTC utilization through behavioral effects for low-demand recipients with less-severe health conditions. The estimates for low-demand recipients in Support levels 1-2, Care levels 1-2, and 2-3 are around 0.2-0.3 and are statistically significant. This result demonstrates that these recipients are affected by the coverage expansion even when they do not face effective price changes. Considering the difference in the extent of coverage expansion shown in the first-stage, these estimates also imply that the larger coverage expansion leads to greater "total" increases in utilization through behavioral effects. This tendency is consistent with the prediction of anchoring effects and heuristic thinking that the larger coverage change results in greater changes in utilization.

Second, the magnitude of behavioral effects decreases gradually as recipients' care-needs level gets higher. The behavioral effects for recipients in Care levels 3-4 are positive, but not significant. For recipients who belong to the highest care-needs levels (Care levels 4-5), the estimates are relatively noisy and not significant. Although non-significance might be attributable to the lower statistical power, these results suggest that recipients with severe health conditions are not affected by behavioral effects. For instance, recipients (and helpers) might be more serious about making care plans when they are in poor health. In this case, recipients are already using LTC necessary for their life. They have little incentive to increase the services unless their utilization is constrained by a coverage limit. However, pinning down the exact mechanisms of the heterogeneity of behavioral effects is beyond the scope of this study.

Third, estimates for high-demand recipients are significant in almost all cases. The magnitudes are generally larger than those of behavioral effects. This strong reaction of high-demand recipients makes sense because the demand of these recipients is constrained by the full price for services beyond insurance coverage. Estimates for high-demand recipients vary among different care-needs levels, with estimates at low care-needs levels tending to be larger than those at high care-needs levels. A one-unit expansion in insurance coverage increases LTC utilization of high-demand recipients by around 0.6-0.8 units at low care-needs levels (Support levels 1-2 or Care levels 1-2), although it increases only 0.3-0.6 units at high care-needs levels. One interpretation of these results is that recipients who exhaust their insurance coverage at low care-needs levels are rare. These exceptional recipients might have demand for services that far exceeds the insurance coverage.

Fourth, except for Care levels 3-4 and 4-5, estimates for all recipients are approximately equal to those of low-demand recipients. As summary statistics and the sample size of this estimation show, a large portion of recipients use LTC services at a sufficiently lower level than the coverage limit, especially those with low care-needs levels. Therefore, the overall effect of insurance coverage can be attributed mainly to behavioral effects. By contrast, the estimates of Care levels 3-4 and 4-5 indicate that the overall effect of insurance coverage for these recipients can be attributable to both behavioral and price effects. As a robustness check, Appendix Table A6 presents estimates of parametric estimation based on a "donut hole" RD design excluding 2-min-wide observations around the thresholds. These estimates show close agreement with those presented in Table 6, which suggests that the potential violation of local randomness has little effect on estimation results.

5.3 Health Consequences of Long-Term Care Utilization

For estimating health effects of LTC, I use the thresholds of standardized care time which create discontinuous variation in insurance coverage as instruments. Appendix Table A7 presents estimates of the first stage effect of insurance coverage on LTC utilization. The focus of this analysis is health effects of LTC utilization during the first certification term. Estimates demonstrate that the instruments have significant effects on LTC utilization for recipients who belong to low care-needs levels (Support levels 1-2, Care levels 1-2 and 2-3), although the effects are not significant for those who belong to high care-needs levels (Care levels 3-4 and 4-5). These results are consistent with estimates for behavioral effects, as shown in Table 6. Therefore, in terms of the health effects, I focus on recipients in Support levels 1-2, Care levels 1-2 and 2-3. It is noteworthy that recipients in the Support level use preventive care, whereas those in the Care level use usual LTC.

Table 7 presents OLS and 2SLS estimates of the health consequences of LTC utilization using standardized care time as a health outcome. Positive values of the estimates imply a negative health effect of LTC because the standardized care time reflects the recipient's need for LTC. OLS estimates suggest that both preventive care (Support level) and usual care (Care level) exert a slightly negative effect on a recipient's health. The 2SLS estimates also tend to have a positive value (a negative effect), with estimates even larger than those of OLS for those with low needs for care. However, the significance of these 2SLS estimates depends on the specification. Estimates are found to be insignificant in many cases. Therefore, one can reasonably infer that few short-run effects of using more LTC on health outcomes exist for either preventive or usual care.

Validity tests of the RD design suggest a manipulation by which care-needs certification examiners avoid assigning recipients to lower care-needs levels. It is then possible that recipients just above the threshold might be more likely to get higher standardized care time at the next term than those just below the threshold, irrespective of LTC utilization. In other words, the exclusion restric-

Table 7: Health Effect of Long-Term Care Utilization

		2SLS				
	OLS (1)	Linear (2)	Quadratic (3)	Cubic (4)	LPR (5)	Obs. (6)
Preventive care						
Support levels 1-2	0.0000	0.0001	0.0010	0.0027	0.0028	4,879
	(0.0001)	(0.0008)	(0.0014)	(0.0026)	(0.0026)	
Usual care						
Care levels 1-2	0.0004***	0.0013	-0.0050	-0.0018	0.0000	5,515
	(0.0001)	(0.0016)	(0.0189)	(0.0027)	(0.0060)	
Care levels 2-3	0.0006***	0.0010	0.0015	0.0006	0.0019	3,140
	(0.0001)	(0.0012)	(0.0010)	(0.0009)	(0.0017)	

Notes: This table presents estimates of β^c in equation 5 using standardized care time at the beginning of the term $s+1$ as a health outcome. The first column represents the OLS estimates and second to fifth columns represent the 2SLS estimates. The 2SLS estimates are presented separetely for different specifications of $f(Caretime_{it})$: linear, quadratic, cubic and LPR representing nonparametric local polynomial regression estimates using the robust confidence intervals proposed by Calonico, Cattaneo, and Titiunik (2014). In the case of OLS, $f(Caretime_{it})$ is linear. Standard errors are shown in parentheses under each estimate. *** p<0.01, ** p<0.05, * p<0.10.

tion of the instrument might be violated when standardized care time is used as a health outcome. It is therefore important to check health effects using different outcome variables. Appendix Table A8 presents OLS and 2SLS estimates of the health effects of LTC, using LTC utilization during the term $s+1$ ($Utilization_{s+1}$) and whether recipients end up entering a nursing home during $s+1$ as health outcomes. The results are consistent with those using standardized care time as health outcomes. Although OLS estimates indicate significant negative health effects of LTC, the 2SLS estimates are mostly not significant, except for the case where LTC utilization is used as an outcome for Care levels 2-3. These results reinforce the argument that using more preventive or usual LTC has little effect on the recipient's health outcomes in the short run.

There are some empirical limitations on estimating the health consequences of LTC in this setting. First, effects of different types of LTC such as home care and day care cannot be identified because only one instrument exists. Therefore, the estimates are expected to be interpreted as the collective effect of all types of LTC services on health outcomes. Second, because of data limitations, estimating health effects of total LTC that includes both LTC services and informal care is beyond the scope of this study. Some earlier studies presented the argument that informal care can be regarded as a substitute for formal LTC service (Mommaerts, 2018). Results of these studies suggest that the change in LTC utilization might be greater than that for all care because the change in utilization might be partially compensated by informal care. Therefore, the estimates presented above must be interpreted as an upper bound of the health effects attributed to the total amount of care a recipient receives.

6 Discussion

6.1 Asymmetric Response to Coverage Expansion and Reduction

From a policy perspective, understanding recipients' responses to both coverage expansion and reduction are important because either policy can be implemented depending on the policy objective. If the effect of coverage reduction is not exactly opposite to that of coverage expansion, then it would be misleading to extrapolate the estimates of coverage expansion simply to the case of coverage reduction.[23] The asymmetric response might become an issue, especially when behavioral effects are considered. For example, the psychological concept of the endowment effect predicts that individuals are less likely to reduce services they are using than to increase them.[24] As shown by the validity test in section 4.4, estimates for coverage reduction are likely to be confounded by unobservable factors. Nevertheless, given the important policy implication of this issue, I discuss behavioral responses to a coverage reduction and their differences from those of coverage expansion in this section. Covariates balance test shows that observed covariates are fairly balanced around thresholds. Therefore, I believe that the estimated effect of coverage reduction can be trustworthy to some degree.

Appendix Tables A9 and A10 respectively reports first-stage and second-stage estimates for coverage reduction. Appendix Table A9 shows that the instruments are statistically significant and valid. I find that the coverage reduction affects LTC utilization asymmetrically with coverage expansion. Most importantly, behavioral effects of coverage reduction are far smaller than those of coverage expansion. In most cases, the estimates are not significant. The coverage reduction does not decrease the service utilization significantly, even for high-demand recipients compared with coverage expansion. Note that these estimates might be overestimated because of the potential

[23] For example, Iizuka and Shigeoka (2019) use variations of patient cost-sharing for children and shows that the response to price changes in opposite directions is not asymmetric.

[24] Kahneman, Knetsch, and Thaler (1991) provide details of the endowment effect.

selection around thresholds.[25] Therefore, the effects of coverage reduction should be small even if the local randomness assumption is satisfied. Weak responses to coverage reduction suggest that recipients are unwilling to give up their current LTC.

The asymmetric response to coverage expansion and reduction leads to important policy implications. Because both low-demand and high-demand recipients are less likely to respond to coverage reduction, the overall effect of coverage reduction tends to be smaller than that of coverage expansion. Therefore, even if policymakers try to constrain service utilization through coverage reduction, the effect might be less than expected from coverage expansion estimates.

6.2 Influence of Care Managers

Anchoring effects and heuristic thinking have been discussed as potential sources of behavioral biases associated with coverage changes. However, in the context of LTCI, care manager practices might also affect LTC utilization, including that of low-demand recipients. This section presents discussions of care manager influence, with argument that the anchoring effect and heuristic thinking are plausible causes of the response of low-demand recipients.

The interpretation of behavioral effects is not reliable if care managers propose a predetermined selection of services to recipients based on care-needs levels, and insurance coverage itself does not affect LTC utilization. Care managers possess specialized knowledge about LTC and play an important role when recipients make a care plan. Therefore, low-demand recipients might be affected more by the predetermined care plan proposed by a care manager than by insurance coverage. One cannot rule out the care manager influence, but the responses of low-demand recipients strongly suggest that insurance coverage itself has a significant effect. Estimation results in Table 6 show that greater coverage expansion leads to greater "total" increase in LTC utilization as long as behavioral effects are statistically significant. Consistency between low-demand recipient responses and the degree of coverage expansion reflect the influence of insurance coverage. If only care managers affected service utilization, then a larger expansion in insurance coverage would not necessarily lead to more significant responses.

[25] Estimates for coverage reduction are overestimated if care-needs certification examiners are screening to reduce care-needs levels of recipients with low utilization and to maintain the levels of those with high utilization.

6.3 Aggregate Impact of Behavioral Effects

The significance of behavioral effects and the fact that many recipients do not exhaust insurance coverage suggest the importance of considering behavioral biases in the design of insurance. To quantify the aggregate impact of behavioral effects, I calculate effects of a hypothetical policy on LTC costs with and without behavioral effects based on a "back-of-the-envelope" calculation.

One policy issue of LTCI is that some recipients exhaust insurance coverage and are then regarded as not being able to receive LTC services sufficient to fulfill their needs. Therefore, I consider the policy of expanding all recipients' insurance coverage by raising their care-needs levels by one stage (except Support level 2 and Care level 5). Following the estimation procedure above, I divide recipients according to whether their utilization is greater than 80% of a coverage limit.[26] Estimates from Table 6 are used as the effect of coverage expansion on low-demand, high-demand, and all recipients. Because the estimates vary with specifications, I calculate both the upper and lower bounds of aggregate effects using the largest and smallest estimates. In choosing the estimates of behavioral effects, those exhibiting negative values are excluded because they might be affected by the inappropriate functional specification. Recipients as of January 2017 are used for calculation.

Appendix Table A11 presents how much the coverage expansion would increase monthly LTC costs at the municipality level. When considering only high-demand recipients, the coverage expansion increases total LTC costs by 1.5-2.5%. However, the effects on low-demand recipients are much greater than high-demand ones: the same coverage expansion increases total costs by 6-9% through behavioral effects. Consequently, the effects on all recipients amount to 9.5-14.5% increases in total costs. This calculation reveals that behavioral effects account for at least 60% of the counterfactual coverage expansion effects.

7 Conclusion

This paper presents an exploration of insurance coverage effects on LTC utilization and its health consequences. Particularly, I estimate the effect of behavioral effects that might induce recipients to respond to coverage changes even when the price they face does not change. The institutional

[26] Although low-demand recipients are defined as those for whom utilization is lower than 50% of coverage limits in the estimation, I change the criterion to 80% for completeness of this analysis.

setting of LTCI in Japan permits the implementation of an RD design to estimate the effect of insurance coverage on the LTC utilization of recipients with different health conditions. To identify behavioral effects, this study specifically examines recipients who do not exhaust their insurance coverage and estimate the effect of coverage expansion on the service utilization of these low-demand recipients. Furthermore, the health consequences of LTC utilization are estimated using the thresholds as instruments.

Estimation results indicate that behavioral biases are the main causes of recipient responses to changes in insurance coverage. For recipients with less-severe health conditions, a one-unit expansion in coverage increases LTC utilization by about 0.3 units through behavioral effects. Overall effects of coverage expansion strongly reflect the magnitude of behavioral effects because most recipients do not exhaust their insurance coverage. For recipients with severe health conditions, however, behavioral effects are not statistically significant. This heterogeneity in behavioral effects suggests that the magnitude of psychological biases might depend on an individual's health condition. The estimates for health effects indicate that LTC utilization has little effect on health, at least in the short run.

The findings presented in this paper highlight the importance of considering non-standard decision-making frameworks in the analysis of social insurance policies. An optimal social insurance policy should reflect the total cause including both price and behavioral effects of the responses to changes in insurance coverage. Decision-makers are influenced significantly by behavioral biases even when they face relatively simple static decision-making. This influence suggests that behavioral biases might be prevalent in many public policy settings. To predict the effect of behavioral biases on public policy, it is useful to find specific mechanisms for these biases. Although I presented some potential mechanisms, identifying the exact mechanisms and quantifying their relative importance is beyond the scope of this study. In terms of health effects, quantifying the effect of LTC utilization on health of family members is also important because the utilization might affect the provision of informal care by the family. These can be interesting avenues for future research.

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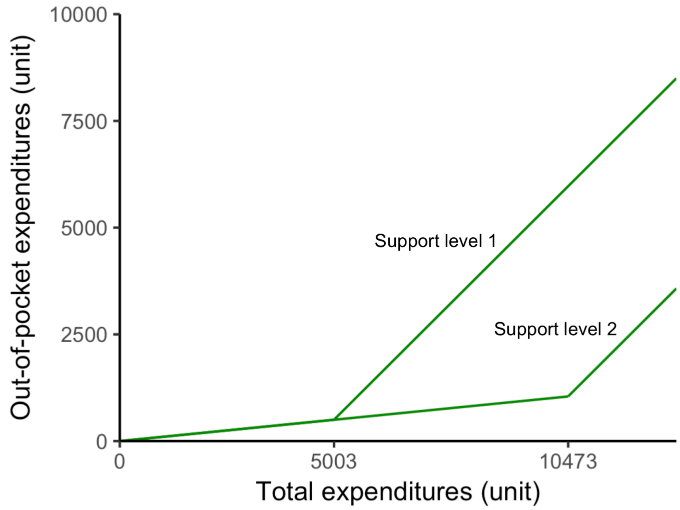
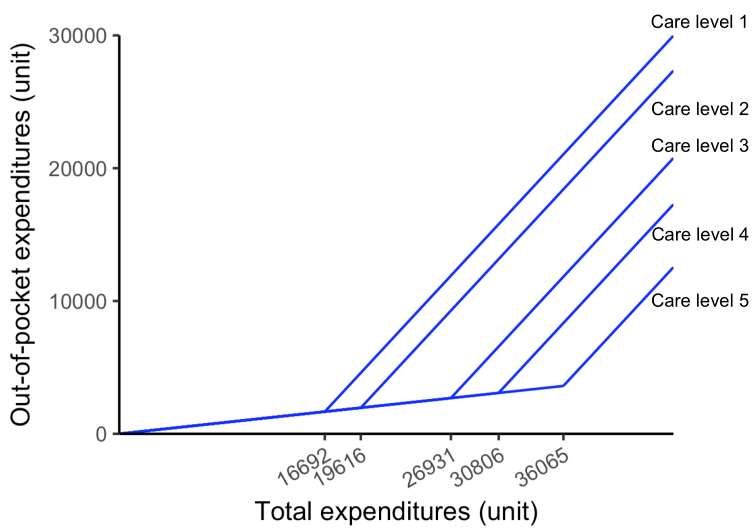
Appendix A: Figures and Tables

Figure A1: Out-of-Pocket Expenditures as a Function of Total Expenditures

(a) Support level

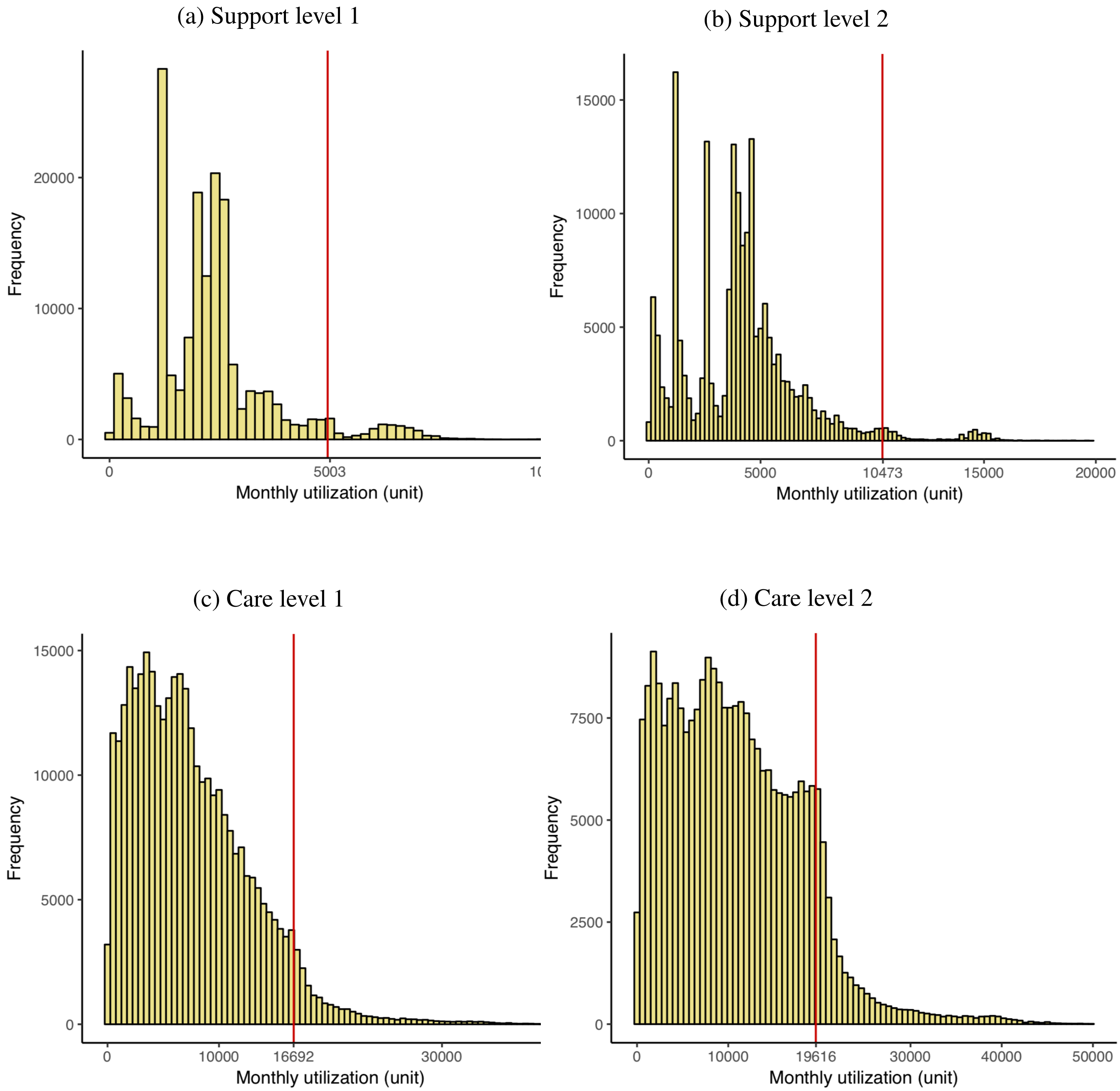


(b) Care level

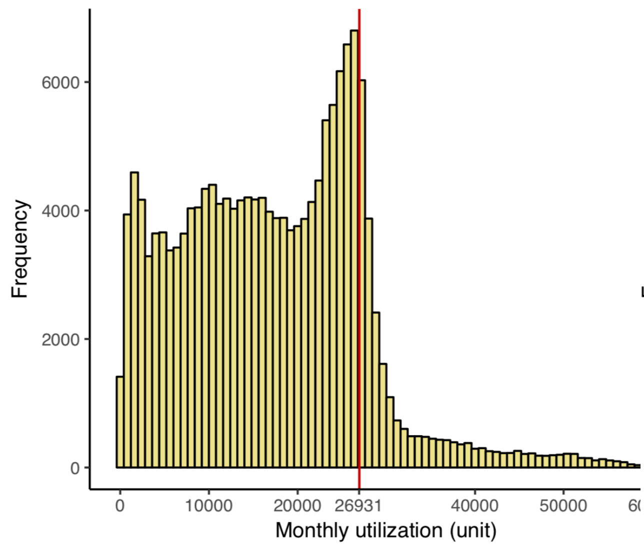


Notes: This figure presents the relation between out-of-pocket expenditure and monthly total expenditure in the case where the coinsurance rate is 10 percent. One unit of LTC services is approximately 10 JPY (0.1 USD).

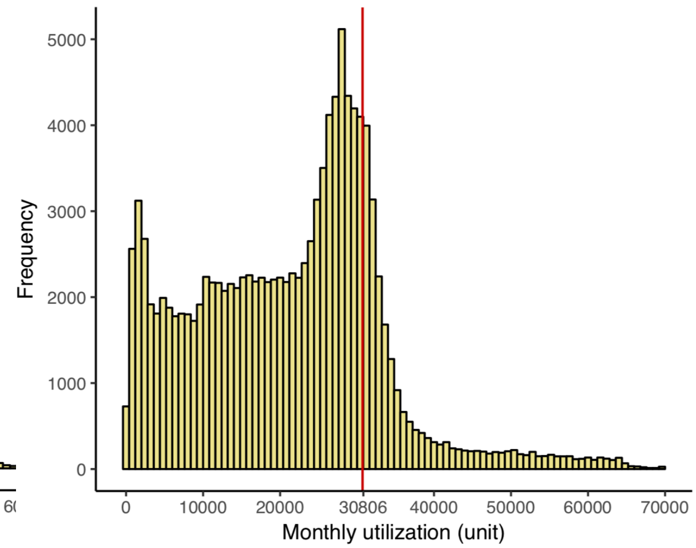
Figure A2: Distribution of Monthly Long-Term Care Utilization



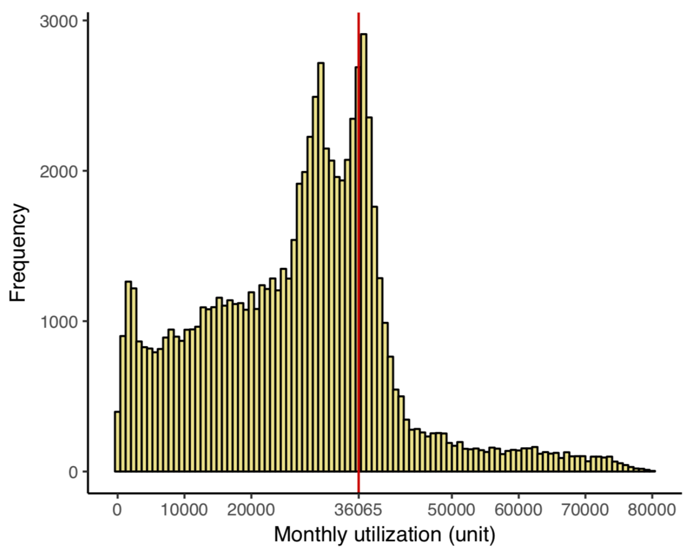
(e) Care level 3



(f) Care level 4

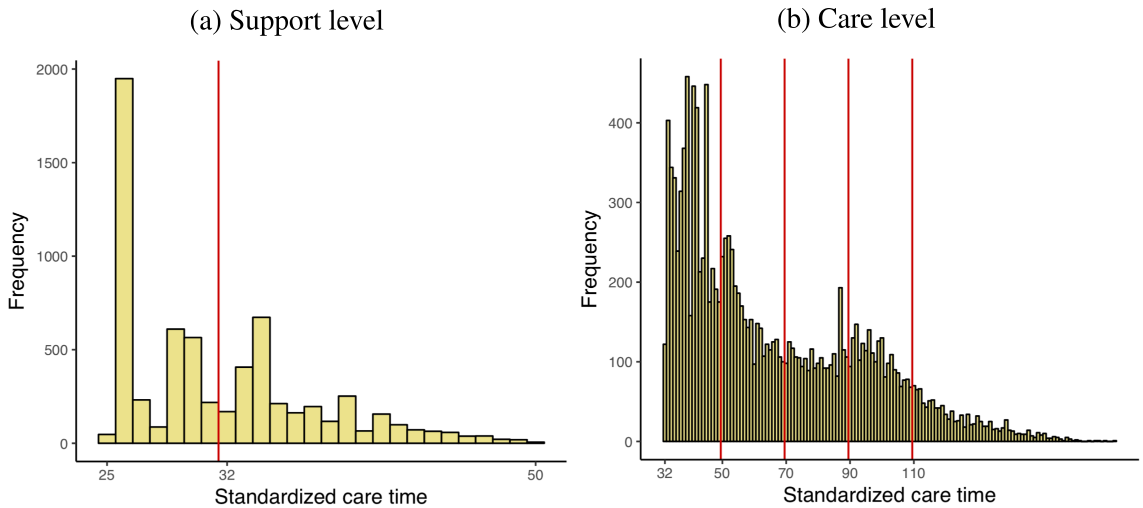


(g) Care level 5



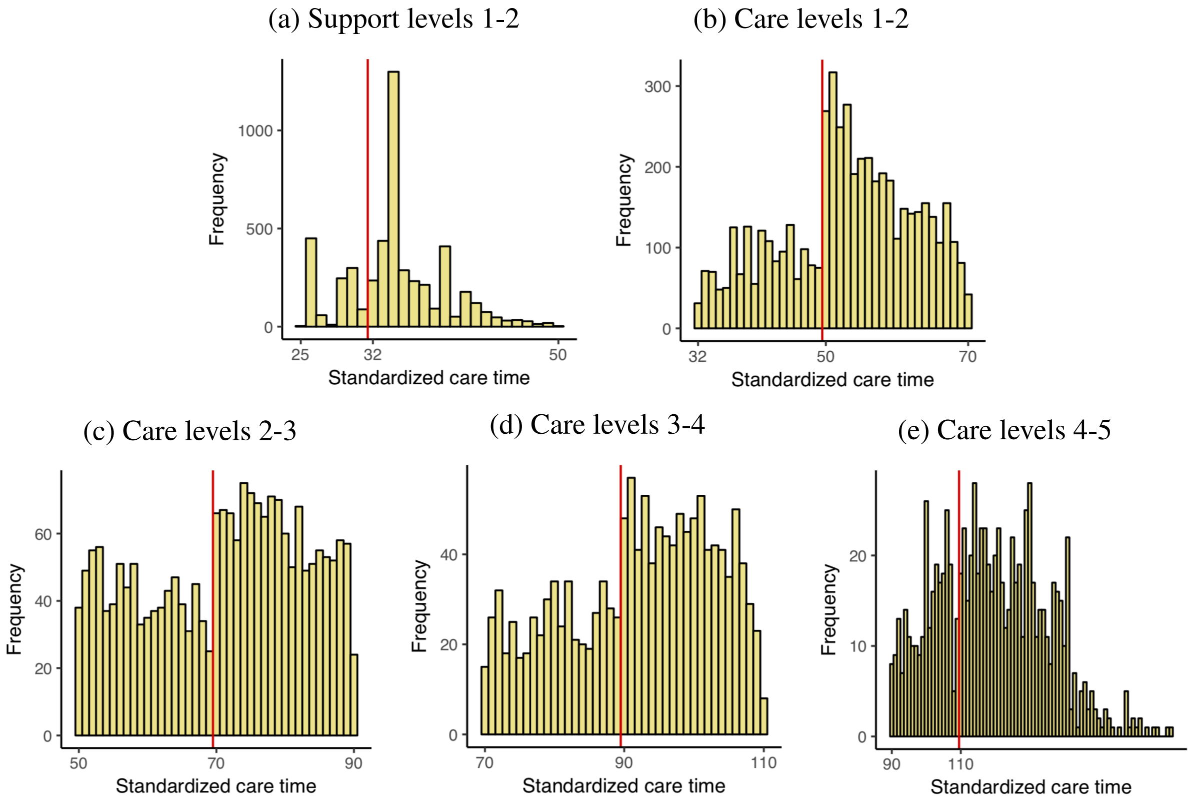
Notes: This figure shows the distribution of monthly LTC utilization for each care-needs level. The red vertical lines indicate monthly coverage limits.

Figure A3: Distribution of Standardized Care Time (First Certification)



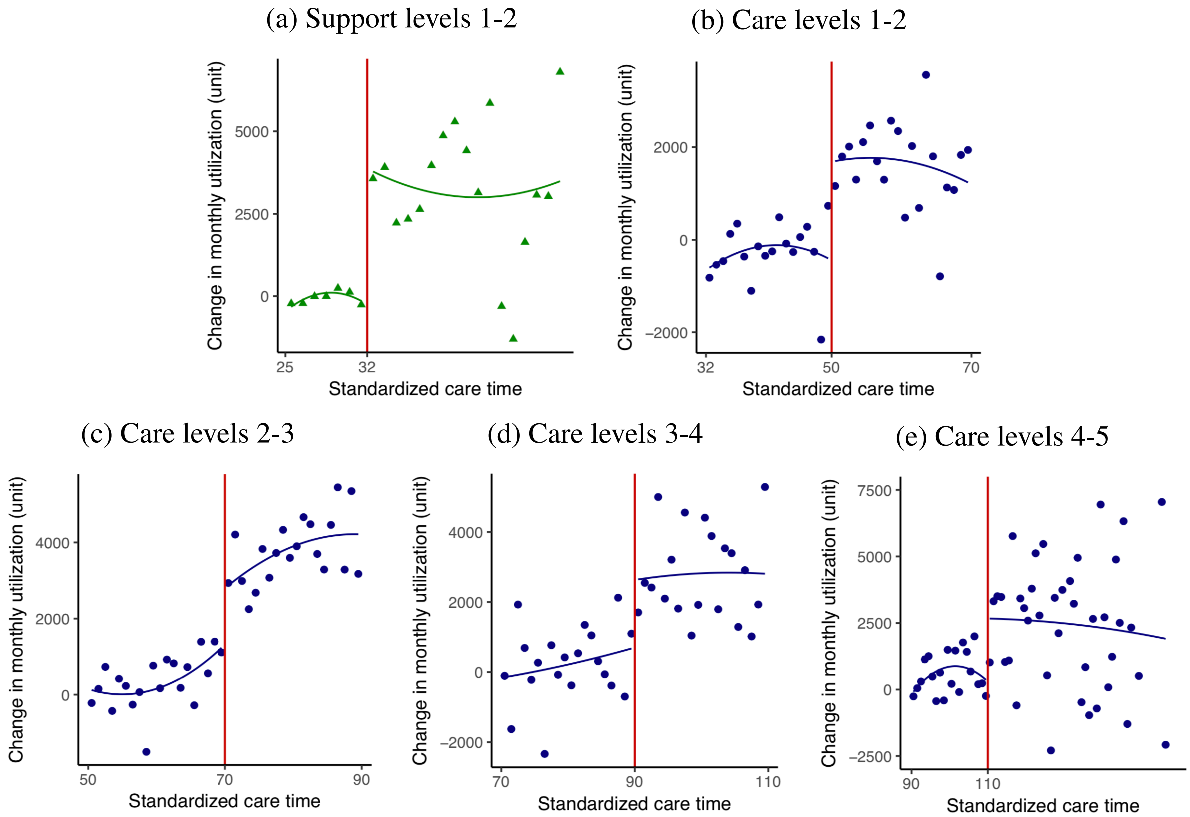
Notes: This figure presents the distribution of standardized care time for Support level (Panel (a)) and Care level (Panel (b)). The distribution is constructed using recipients who take their first care-needs certification. The bin width is 1 min of standardized care time.

Figure A4: Distribution of Standardized Care Time (Coverage Reduction, Low-Demand)



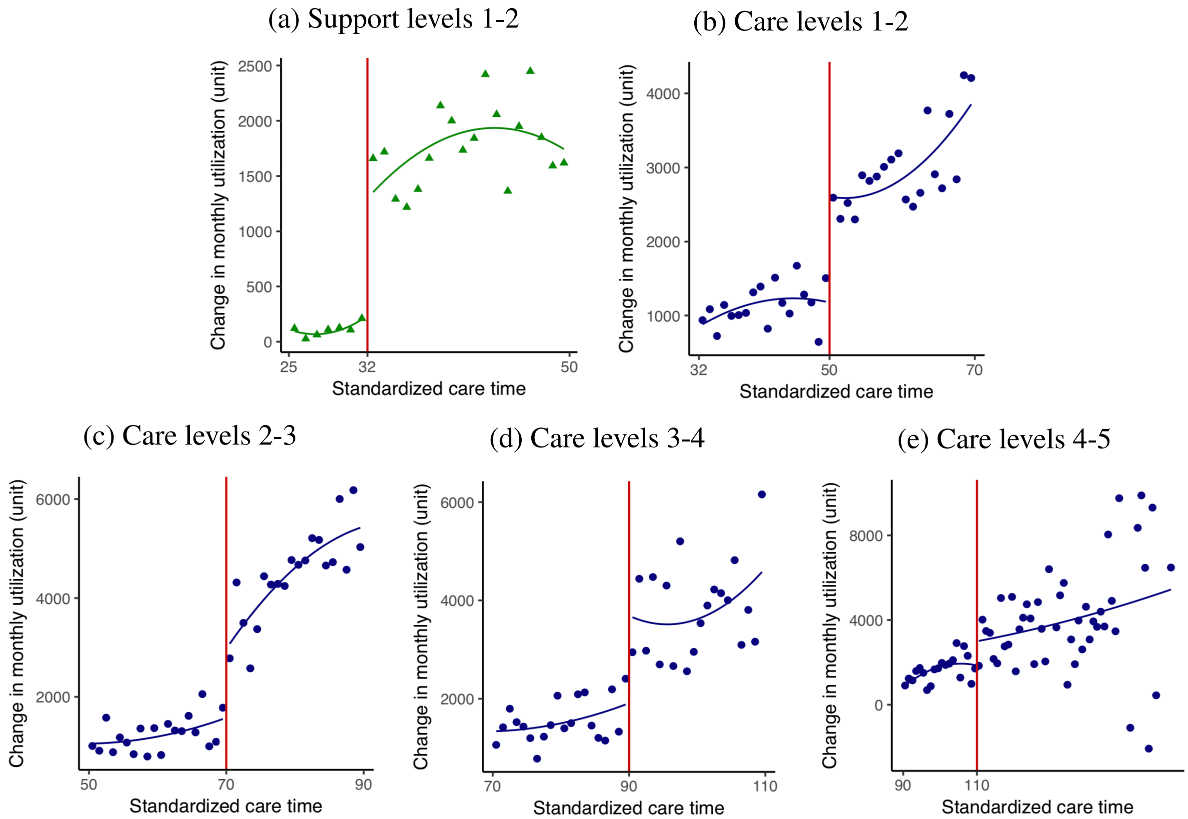
Notes: This figure presents the distribution of standardized care time for each care-needs level. The distribution is constructed using the (modified) low-demand recipients after reclassification of care-needs levels (either the same or one-stage lower level). The bin width is 1 min of standardized care time.

Figure A5: Changes in Long-Term Care Utilization (High-demand)



Notes: This figure presents effects of expanding insurance coverage on LTC utilization using high-demand recipients who end up being either the same or one stage worse after the reclassification. I divide standardized care time into 1 min-wide interval (bins). Each plot represents a local average of changes in monthly LTC utilization before and after reclassification. I plot the local average for both the Support level (Panel (a)) and the Care level (Panels (b)-(e)) and a quadratic prediction is fitted on plots for each care-needs level.

Figure A6: Changes in Long-Term Care Utilization (All Recipients)



Notes: This figure presents effects of expanding insurance coverage on LTC utilization using all recipients who end up being either the same or one stage worse after the reclassification. I divide standardized care time into 1 min-wide interval (bins). Each plot represents a local average of changes in monthly LTC utilization before and after reclassification. I plot the local average for both the Support level (Panel (a)) and the Care level (Panel (b)-(e)) and a quadratic prediction is fitted on plots for each care-needs level.

Table A1: Density Test

	All recipients		Low-demand		High-demand	
	Est. (1)	SE (2)	Est. (3)	SE (4)	Est. (5)	SE (6)
A. Baseline sample						
Support levels 1-2	-0.0041	(0.0063)				
Care levels 1-2	0.0251***	(0.0013)				
Care levels 2-3	0.0057**	(0.0026)				
Care levels 3-4	0.0014	(0.0026)				
Care levels 4-5	-0.0003	(0.0022)				
B. First certification						
Support levels 1-2	0.0313	(0.0402)				
Care levels 1-2	0.0403***	(0.0096)				
Care levels 2-3	0.0076	(0.0066)				
Care levels 3-4	0.0042	(0.0028)				
Care levels 4-5	0.0015	(0.0038)				
C. Coverage expansion						
Support levels 1-2	-0.0293	(0.0257)	-0.0256	(0.0166)	0.0284**	(0.0128)
Care levels 1-2	0.0102	(0.0109)	0.0013	(0.0135)	0.0105	(0.0140)
Care levels 2-3	0.0006	(0.0019)	0.0058	(0.0047)	0.0070	(0.0052)
Care levels 3-4	-0.0027	(0.0051)	0.0024	(0.0102)	-0.0018	(0.0072)
Care levels 4-5	0.0007	(0.0055)	0.0094	(0.0098)	0.0040	(0.0068)
D. Coverage reduction						
Support levels 1-2	0.3708***	(0.0103)	0.0953***	(0.0098)	0.4581***	(0.0161)
Care levels 1-2	0.0641***	(0.0048)	0.0560***	(0.0039)	0.0570***	(0.0072)
Care levels 2-3	0.0283***	(0.0048)	0.0182***	(0.0046)	0.0232***	(0.0058)
Care levels 3-4	0.0247***	(0.0066)	0.0180***	(0.0061)	0.0262***	(0.0081)
Care levels 4-5	0.0100*	(0.0056)	0.0163**	(0.0064)	0.0119**	(0.0050)

Notes: This table presents results of the density test proposed by Cattaneo, Jansson, and Ma (2020). Panel A and B respectively show results for the distribution of standardized care time using all recipients-term and first care-needs certification. Panel C and D show results for the distribution after reclassification of care-needs levels. The first and second columns show results for entire recipients. The rest of the columns show estimates for low-demand and high-demand recipients separately. Low-demand recipients are those whose average monthly LTC utilization during the prior certification term is less than 50% of a given coverage limit. High-demand recipients are those whose average monthly LTC utilization during the prior certification term is higher than 80% of a given coverage limit. *** p<0.01, ** p<0.05, * p<0.10.

Table A2: Covariates Balance Tests (All Baseline Samples)

	Linear		Quadratic			
	Coeff. (1)	SE (2)	Coeff. (3)	SE (4)	Obs. (5)	Cluster (6)
Support levels 1-2						
Age	-0.234	(0.193)	1.007***	(0.356)		
Female	0.023	(0.011)	-0.070***	(0.023)	38,025	15,646
20% coinsurance	0.001	(0.006)	0.042***	(0.011)		
Care levels 1-2						
Age	-0.411	(0.163)	-0.335	(0.239)		
Female	-0.031***	(0.008)	-0.002	(0.013)	51,367	28,607
20% coinsurance	0.001	(0.005)	-0.003	(0.007)		
Care levels 2-3						
Age	-0.078	(0.220)	-0.346	(0.337)		
Female	0.019	(0.012)	0.011	(0.017)	36,613	22,848
20% coinsurance	-0.005	(0.006)	-0.019**	(0.009)		
Care levels 3-4						
Age	-0.667***	(0.232)	-0.675**	(0.336)		
Female	0.014	(0.012)	0.021	(0.017)	27,469	18,801
20% coinsurance	-0.006	(0.006)	-0.005	(0.009)		
Care levels 4-5						
Age	-0.381	(0.277)	-0.152	(0.389)		
Female	0.001	(0.013)	-0.001	(0.019)	20,689	14,371
20% coinsurance	-0.005	(0.007)	0.004	(0.010)		

Notes: This table presents estimates of covariate balance tests for the linear and quadratic RD specification from equation 7, using all recipients in the baseline sample. *** p<0.01, ** p<0.05, * p<0.10.

Table A3: Covariates Balance Tests (First Certification)

	Linear		Quadratic		
	Coeff. (1)	SE (2)	Coeff. (3)	SE (4)	Obs. (5)
Support levels 1-2					
Age	0.239	(0.368)	1.629**	(0.693)	
Female	0.037	(0.025)	-0.037	(0.048)	6,535
20% coinsurance	0.020	(0.013)	0.050**	(0.025)	
Care levels 1-2					
Age	-1.857***	(0.391)	-1.973***	(0.586)	
Female	-0.039	(0.022)	0.036	(0.033)	8,465
20% coinsurance	0.013	(0.013)	-0.029	(0.020)	
Care levels 2-3					
Age	0.187	(0.568)	0.748	(0.862)	
Female	-0.022	(0.029)	-0.051	(0.044)	5,312
20% coinsurance	-0.008	(0.016)	-0.011	(0.023)	
Care levels 3-4					
Age	-0.465	(0.584)	-0.090	(0.870)	
Female	-0.036	(0.030)	-0.035	(0.044)	4,201
20% coinsurance	0.013	(0.017)	0.011	(0.025)	
Care levels 4-5					
Age	-0.823	(0.691)	-1.363	(1.006)	
Female	-0.065*	(0.034)	-0.043	(0.049)	3,199
20% coinsurance	0.024	(0.019)	0.033	(0.027)	

Notes: This table presents estimates of covariate balance tests for the linear and quadratic RD specification from equation 7, using recipients who take their first care-needs certification. *** p<0.01, ** p<0.05, * p<0.10.

Table A4: Covariates Balance Tests (Coverage Reduction)

	All recipients				Low-demand recipients				High-demand recipients			
	Linear		Quadratic		Linear		Quadratic		Linear		Quadratic	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Support levels 1-2												
Age	-0.846**	(0.379)	0.874	(0.732)	-0.295	(0.530)	1.466	(0.926)	-1.494***	(0.526)	0.247	(1.021)
Female	-0.018	(0.022)	-0.117***	(0.045)	-0.029	(0.029)	-0.152***	(0.060)	0.001	(0.034)	-0.077	(0.066)
20% coinsurance	0.021*	(0.011)	0.033	(0.022)	0.023	(0.016)	0.023	(0.033)	0.019	(0.015)	0.045	(0.029)
Observation	10,846				4,951				5,895			
Cluster	5,576				3,063				3,181			
Care levels 1-2												
Age	0.138	(0.474)	0.188	(0.736)	-0.409	(0.524)	-0.039	(0.798)	1.584	(1.134)	0.854	(1.879)
Female	-0.003	(0.026)	0.001	(0.040)	-0.018	(0.029)	-0.050	(0.044)	0.035	(0.058)	0.206**	(0.093)
20% coinsurance	0.004	(0.014)	0.009	(0.021)	-0.001	(0.016)	0.018	(0.024)	0.022	(0.031)	-0.034	(0.042)
Observation	7,248				5,100				2,148			
Cluster	5,816				4,194				1,779			
Care levels 2-3												
Age	0.065	(0.674)	-0.029	(1.043)	-1.037	(0.941)	-1.815	(1.486)	1.130	(0.975)	1.710	(1.449)
Female	0.055*	(0.032)	0.093*	(0.048)	0.047	(0.046)	0.080	(0.070)	0.043	(0.045)	0.090	(0.067)
20% coinsurance	-0.010	(0.018)	-0.039	(0.026)	-0.027	(0.027)	-0.039	(0.043)	0.017	(0.022)	-0.030	(0.031)
Observation	4,697				2,083				2,614			
Cluster	3,759				1,766				2,114			
Care levels 3-4												
Age	-0.572	(0.541)	-0.804	(0.796)	2.078**	(0.923)	1.507	(1.344)	-1.970***	(0.663)	-1.883*	(0.981)
Female	0.019	(0.028)	-0.004	(0.040)	0.013	(0.049)	0.020	(0.071)	0.022	(0.034)	-0.018	(0.049)
20% coinsurance	-0.005	(0.014)	-0.008	(0.020)	0.046*	(0.025)	-0.032	(0.017)	-0.041**	(0.017)	-0.012	(0.024)
Observation	4,813				1,790				3,023			
Cluster	3,867				1,499				2,479			
Care levels 4-5												
Age	-0.654	(0.862)	1.326	(1.242)	-2.531	(1.692)	-0.282	(2.583)	0.135	(0.969)	1.937	(1.340)
Female	0.025	(0.039)	0.089	(0.056)	-0.034	(0.067)	-0.110	(0.097)	0.052	(0.048)	0.190***	(0.069)
20% coinsurance	-0.014	(0.019)	-0.021	(0.030)	-0.017	(0.032)	0.025	(0.044)	-0.012	(0.024)	-0.045	(0.040)
Observation	2,701				897				1,804			
Cluster	2,013				706				1,370			

Notes: This table presents estimates of covariate balance tests for the linear and quadratic RD specification from equation 7. These estimations use recipients who are used for analyzing coverage reduction after reclassification of care-needs levels. Low-demand recipients are those whose average monthly LTC utilization during the earlier certification term is less than 50% of a coverage limit of the one-stage lower care-needs level. High-demand recipients are those whose average monthly LTC utilization during a previous certification term is higher than 80% of a coverage limit of the one-stage lower care-needs level. *** p<0.01, ** p<0.05, * p<0.10.

Table A5: First-Stage Estimates for Coverage Expansion

	Linear		Quadratic		Cubic		LPR			
	Coeff. (1)	SE (2)	Coeff. (3)	SE (4)	Coeff. (5)	SE (6)	Coeff. (7)	SE (8)	Obs. (9)	Cluster (10)
Support levels 1-2										
All recipients	5,098.4***	(43.0)	4,931.8***	(108.2)	4,854.9***	(220.1)	4,602.6***	(409.8)	110,120	5,631
Low-demand	5,107.0***	(55.6)	4,915.1***	(42.8)	4,833.9***	(306.6)	4,415.9***	(327.9)	71,747	4,039
High-demand	4,939.3***	(159.1)	5,018.9***	(292.1)	5,407.0***	(311.5)	5,730.6***	(199.7)	8,548	538
Care levels 1-2										
All recipients	2,869.4***	(17.3)	2,901.9***	(20.2)	2,858.8***	(24.7)	2,842.9***	(29.7)	192,276	10,454
Low-demand	2,856.4***	(23.2)	2,878.9***	(28.9)	2,819.4***	(37.4)	2,801.4***	(45.7)	121,190	7,136
High-demand	2,797.2***	(57.7)	2,878.0***	(66.2)	2,884.2***	(57.5)	2,902.8***	(12.1)	22,236	1,354
Care levels 2-3										
All recipients	6,375.9***	(77.3)	6,118.4***	(139.6)	5,726.9***	(212.1)	5,483.4***	(319.3)	110,245	6,439
Low-demand	6,532.6***	(123.0)	6,368.9***	(216.4)	6,121.5***	(321.0)	5,966.3***	(479.3)	50,457	2,934
High-demand	5,985.0***	(165.6)	5,747.7***	(288.7)	5,351.4***	(421.9)	5,202.5***	(611.7)	28,225	1,920
Care levels 3-4										
All recipients	3,327.6***	(68.9)	3,285.3***	(102.4)	3,188.9***	(136.0)	3,117.7***	(199.8)	63,109	3,867
Low-demand	3,401.7***	(109.3)	3,449.2***	(160.9)	3,432.9***	(223.2)	3,232.5***	(282.7)	20,085	1,217
High-demand	3,257.9***	(108.9)	3,204.1***	(152.8)	3,056.0***	(194.2)	3,095.3***	(210.1)	25,902	1,725
Care levels 4-5										
All recipients	4,457.5***	(91.5)	4,252.5***	(145.8)	4,176.3***	(202.1)	4,199.7***	(258.3)	43,881	2,700
Low-demand	4,243.4***	(219.2)	4,006.3***	(343.6)	3,869.5***	(490.4)	3,428.2***	(731.7)	10,760	686
High-demand	4,434.0***	(128.9)	4,220.4***	(197.0)	4,178.9***	(262.7)	4,312.8***	(277.1)	22,016	1,433

Notes: This table presents the first-stage estimates of β_0^c in equation 4. The first to sixth columns show estimates for different specifications of $f_0(Caretime_{it})$: linear, quadratic, and cubic respectively. The seventh and eighth columns show the nonparametric local polynomial regression (LPR) estimates using the robust confidence intervals proposed by Calonico, Cattaneo, and Titiunik (2014). *** p<0.01, ** p<0.05, * p<0.10.

Table A6: Effects of Coverage Expansion on Long-Term Care Utilization (Donut-hole)

	Linear		Quadratic		Cubic			
	Coeff. (1)	SE (2)	Coeff. (3)	SE (4)	Coeff. (5)	SE (6)	Obs. (7)	Cluster (8)
Support levels 1-2								
All recipients	0.204***	(0.017)	0.149***	(0.038)	0.218***	(0.078)	101,957	5,247
Low-demand	0.171***	(0.018)	0.140***	(0.040)	0.207***	(0.074)	66,512	3,766
High-demand	0.387***	(0.083)	0.060	(0.187)	-0.379	(0.471)	7,680	481
Care levels 1-2								
All recipients	0.310***	(0.057)	0.369***	(0.095)	0.211	(0.156)	178,922	9,864
Low-demand	0.206***	(0.069)	0.273**	(0.114)	0.105	(0.191)	112,930	6,710
High-demand	0.811***	(0.212)	0.819**	(0.366)	0.616	(0.573)	20,672	1270
Care levels 2-3								
All recipients	0.274***	(0.042)	0.242***	(0.071)	0.337***	(0.120)	105,603	6,218
Low-demand	0.184***	(0.063)	0.297***	(0.109)	0.273	(0.183)	48,689	2,851
High-demand	0.331***	(0.084)	0.143	(0.136)	0.383*	(0.230)	26,933	1,837
Care levels 3-4								
All recipients	0.551***	(0.126)	0.645***	(0.204)	0.799**	(0.331)	59,352	3,666
Low-demand	0.352	(0.221)	0.888**	(0.355)	0.883	(0.541)	19,055	1,150
High-demand	0.810***	(0.196)	0.706**	(0.323)	0.838	(0.584)	24,058	1,632
Care levels 4-5								
All recipients	0.172	(0.104)	0.214	(0.171)	0.330	(0.262)	42,188	2,607
Low-demand	0.025	(0.245)	-0.400	(0.412)	-0.709	(0.608)	10,445	669
High-demand	0.332**	(0.136)	0.439**	(0.221)	0.593	(0.364)	21,005	1,375

Notes: This table presents second-stage estimates of β^c in equation 3 excluding 2-min-wide observations around the thresholds. The first to sixth columns present the estimates for different specifications of $f(Caretime_{it})$: linear, quadratic, and cubic. Low-demand recipients are those for which average monthly LTC utilization during the previous certification term was less than 50% of a given coverage limit. High-demand recipients are those for which the average monthly LTC utilization during the prior certification term was more than 80% of a given coverage limit. *** p<0.01, ** p<0.05, * p<0.10.

Table A7: First-Stage Estimates for the Health Effects of Long-Term Care Utilization

	Standardized care time				Utilization / Nursing home					
	Linear (1)	Quadratic (2)	Cubic (3)	LPR (4)	Linear (5)	Quadratic (6)	Cubic (7)	LPR (Util) (8)	LPR (NH) (9)	Obs. (10)
Support levels 1-2	1,104.9***	1,134.7***	1,049.8***	760.7***	1,105.0***	1,135.1***	1,050.9***	706.6**	714.0**	4,879
	(100.4)	(184.6)	(297.5)	(275.6)	(100.4)	(184.6)	(297.6)	(291.5)	(287.3)	
Care levels 1-2	900.6***	322.4	1,199.9**	546.1	875.4***	572.6	1,247.6**	465.5	588.5	5,515
	(264.5)	(402.7)	(552.2)	(688.2)	(263.3)	(400.8)	(549.7)	(681.6)	(672.8)	
Care levels 2-3	1,541.8***	3,063.8***	4,180.8***	2,964.2**	1,482.5***	2,885.7***	4,089.6***	3,354.2**	3,359.9***	3,140
	(487.2)	(745.2)	(1,022.1)	(1,352.1)	(481.4)	(736.7)	(1,010.1)	(1,075.8)	(1,073.9)	
Care levels 3-4	617.0	-626.3	-2,036.5	-2,162.2	717.0	-567.7	-1,730.8	-1,725.0	-2,167.7	2,257
	(669.4)	(985.7)	(1,338.8)	(1,395.3)	(638.8)	(940.7)	(1,278.3)	(1,316.1)	(1,462.2)	
Care levels 4-5	256.2	1108.3	-1,500.7	-2,743.2	428.1	1,450.5	-846.0	-1,384.5	-1,364.0	1,532
	(987.1)	(1,413.8)	(1,813.0)	(2,802.8)	(900.5)	(1,289.7)	(1,654.6)	(2,146.7)	(2,204.3)	

Notes: This table presents the first-stage estimates β_0^c in equation 6. The first to fourth column show estimates for the case of using standardized care time as a health outcome. The fifth to ninth columns represent the case of utilization or whether to enter a nursing home. Estimates are separately presented for different specifications of $f(Caretime_{it})$: linear, quadratic, cubic and LPR representing nonparametric local polynomial regression estimates using the robust confidence intervals proposed by Calonico, Cattaneo, and Titiunik (2014). The eighth and ninth columns represent the estimates of LPR for the case of utilization and nursing home respectively. Standard errors are shown in parentheses under each estimate. *** p<0.01, ** p<0.05, * p<0.10.

Table A8: The Health Effect of Long-Term Care Utilization (2)

	Utilization					Nursing home					
		2SLS					2SLS ($\times 10^3$)				
	OLS (1)	Linear (2)	Quadratic (3)	Cubic (4)	LPR (5)	OLS ($\times 10^3$) (6)	Linear (7)	Quadratic (8)	Cubic (9)	LPR (10)	Obs. (11)
<u>Preventive care</u>											
Support levels 1-2	0.882***	-0.060	0.261	0.463	-0.192	0.014***	-0.002	-0.008	0.020	0.015	4,879
	(0.053)	(0.244)	(0.420)	(0.719)	(0.823)	(0.003)	(0.010)	(0.017)	(0.030)	(0.036)	
<u>Usual care</u>											
Care levels 1-2	0.877***	0.509	-0.052	0.321	-0.894	0.012***	0.016	0.003	-0.022	-0.086	5,515
	(0.017)	(0.342)	(1.590)	(0.533)	(2.054)	(0.001)	(0.018)	(0.069)	(0.031)	(0.110)	
Care levels 2-3	0.816***	0.550*	1.052***	0.773***	0.840***	0.011***	-0.001	0.005	0.002	0.005	3,140
	(0.019)	(0.294)	(0.229)	(0.214)	(0.320)	(0.001)	(0.017)	(0.013)	(0.012)	(0.018)	

Notes: This table presents estimates of β^c in equation 5 using utilization or whether to enter a nursing home as a health outcome. The first to fifth columns represent the estimates for the case of using LTC utilization as a health outcome. The sixth to tenth columns represent the case of whether to enter a nursing home. The first and sixth columns represent the OLS estimates and other columns represent the 2SLS estimates. The 2SLS estimates are presented separately for different specifications of $f(Caretime_{it})$: linear, quadratic, cubic and LPR representing nonparametric local polynomial regression estimates using the robust confidence intervals proposed by Calonico, Cattaneo, and Titiunik (2014). In the case of OLS, $f(Caretime_{it})$ is linear. Standard errors are shown in parentheses under each estimate. *** p<0.01, ** p<0.05, * p<0.10.

Table A9: First-Stage Estimates for Coverage Reduction

	Linear		Quadratic		Cubic		LPR			
	Coeff. (1)	SE (2)	Coeff. (3)	SE (4)	Coeff. (5)	SE (6)	Coeff. (7)	SE (8)	Obs. (9)	Cluster (10)
Support levels 1-2										
All recipients	-2,575.9***	(136.6)	-2,141.7***	(264.4)	-1,689.6***	(455.8.7)	-2,361.8***	(614.9)	109,026	5,576
Low-demand	-3,092.4***	(186.0)	-2,781.9***	(378.2)	-1,997.1***	(643.7)	-2,512.1***	(438.5)	50,115	3,063
High-demand	-2,019.0***	(194.7)	-1,507.0***	(359.6)	-1,597.4***	(621.5)	-1,593.5***	(606.7)	58,911	3,181
Care levels 1-2										
All recipients	-2,911.0***	(28.9)	-3,093.0***	(36.7)	-2,928.2***	(43.7)	-2,983.7***	(47.1)	101,012	5,816
Low-demand	-2,938.0***	(33.2)	-3,064.8***	(41.4)	-2,915.5***	(47.8)	-2,961.1***	(50.8)	71,773	4,194
High-demand	-2,848.6***	(59.4)	-3,173.7***	(82.5)	-2,997.3***	(103.4)	-3,119.0***	(106.5)	29,248	1,779
Care levels 2-3										
All recipients	-3,007.7***	(219.0)	-2,252.0***	(316.5)	-1,802.5***	(410.1)	-1,720.4***	(503.3)	66,433	3,759
Low-demand	-3,944.8***	(290.9)	-3,282.1***	(447.3)	-3,407.1***	(610.7)	-2,897.6***	(716.1)	30,475	1,766
High-demand	-2,002.9***	(308.9)	-1,152.1***	(402.8)	-231.7	(470.5)	-626.3	(501.3)	35,958	2,114
Care levels 3-4										
All recipients	-1,569.1***	(130.2)	-1,359.3***	(190.0)	-1,104.4***	(245.3)	-1,134.7***	(291.1)	44,911	2,609
Low-demand	-2,029.1***	(187.9)	-1,522.3***	(275.8)	-1,423.0***	(367.1)	-1,512.1***	(474.7)	19,555	1,149
High-demand	-1,222.8***	(177.5)	-1,240.7***	(257.0)	-863.0***	(326.2)	-817.3	(376.0)	25,356	1,528
Care levels 4-5										
All recipients	-1,232.8***	(195.2)	-1,290.4***	(277.6)	-1,134.0***	(362.5)	-390.2	(462.2)	36,574	2,013
Low-demand	-1,696.8***	(334.7)	-1,685.4***	(538.8)	-1,104.3**	(698.2)	-1,336.3	(883.5)	12,582	706
High-demand	-988.6***	(257.5)	-1,142.4***	(323.6)	-1,274.4***	(421.7)	-1,209.3***	(391.2)	23,992	1,370

Notes: This table presents the first-stage estimates of β_0^c in equation B.2. The first to sixth columns represent estimates for different specifications of $f_0(Caretime_{it})$: linear, quadratic, and cubic respectively. The seventh and eighth columns show the nonparametric local polynomial regression (LPR) estimates using the robust confidence intervals proposed by Calonico, Cattaneo, and Titiunik (2014). *** p<0.01, ** p<0.05, * p<0.10.

Table A10: The Effects of Coverage Reduction on Long-Term Care Utilization

	Linear		Quadratic		Cubic		LPR			
	Coeff. (1)	SE (2)	Coeff. (3)	SE (4)	Coeff. (5)	SE (6)	Coeff. (7)	SE (8)	Obs. (9)	Cluster (10)
Support levels 1-2										
All recipients	0.228***	(0.033)	0.175***	(0.086)	0.510***	(0.199)	0.270	(0.213)	109,026	5,574
Low-demand	0.066***	(0.026)	0.018	(0.059)	-0.138	(0.161)	0.007	(0.080)	50,115	3,063
High-demand	0.528***	(0.055)	0.520***	(0.154)	0.997***	(0.302)	0.861	(0.241)	58,911	3,181
Care levels 1-2										
All recipients	0.192***	(0.063)	0.129	(0.094)	0.119	(0.134)	0.105	(0.157)	101,012	5,816
Low-demand	0.208***	(0.060)	0.127	(0.088)	-0.006	(0.119)	0.020	(0.133)	71,773	4,194
High-demand	0.284	(0.205)	0.394	(0.322)	0.950***	(0.471)	0.806	(0.539)	29,248	1,779
Care levels 2-3										
All recipients	0.142	(0.109)	0.230	(0.219)	0.402	(0.360)	0.732*	(0.506)	66,433	3,759
Low-demand	0.057	(0.093)	0.157	(0.161)	0.119	(0.204)	0.241	(0.240)	30,475	1,766
High-demand	0.404	(0.273)	0.692	(0.713)	5.204	(9.947)	3.875	(3.294)	35,958	2,114
Care levels 3-4										
All recipients	0.381	(0.240)	0.240	(0.483)	0.188	(0.818)	-0.089	(0.945)	44,911	2,609
Low-demand	0.174	(0.256)	0.368	(0.482)	0.121	(0.671)	0.186	(0.695)	19,555	1,149
High-demand	0.733	(0.502)	0.326	(0.813)	0.309	(1.632)	-0.747	(2.048)	25,356	1,528
Care levels 4-5										
All recipients	-0.779*	(0.469)	-0.584	(0.647)	-1.450	(1.010)	-4.903	(3.182)	36,574	2,013
Low-demand	-0.941	(0.502)	-1.396*	(0.825)	-2.447	(1.957)	-2.735	(2.052)	12,582	706
High-demand	-0.648	(0.741)	-0.135	(0.848)	-1.068	(1.013)	-0.329	(1.030)	23,992	1,370

Notes: This table presents second-stage estimates of β^c in equation B.1. The first to sixth columns present the estimates for different specifications of $f(Caretime_{it})$: linear, quadratic and cubic. The seventh and eighth columns show the nonparametric local polynomial regression (LPR) estimates using the robust confidence intervals proposed by Calonico, Cattaneo, and Titiunik (2014). Low-demand recipients are those whose average monthly LTC utilization during the previous certification term was less than 50% of a given coverage limit. High-demand recipients are those whose average monthly LTC utilization during the prior certification term was more than 80% of a given coverage limit. *** p<0.01, ** p<0.05, * p<0.10.

Table A11: Effects of Counterfactual Policy on Monthly Long-Term Care Costs

High-Demand		Low-Demand		All Recipients	
Lower	Upper	Lower	Upper	Lower	Upper
(1)	(2)	(3)	(4)	(5)	(6)
\$0.30 million (1.52%)	\$0.49 million (2.53%)	\$1.15 million (5.90%)	\$1.80 million (9.27%)	\$1.84 million (9.48%)	\$2.83 million (14.59%)

Notes: This table presents the expected increase in monthly LTC costs resulting from the counterfactual policy which expands all recipients' insurance coverage by one-stage (except Support level 2 and Care level 5). The values in parenthesis represent the percentage increases in total cost of home-based LTC. The upper and lower bound are respectively calculated using the largest and smallest estimates in Table 6, excluding those with a negative value. The approximation of 1 unit = 0.1 USD is assumed for the calculation.

Appendix B: Estimation of Coverage Reduction

When recipients face a coverage reduction, they are influenced by price effects if their service utilization is higher than the *one-stage lower* coverage limit. Therefore, the first step focuses on recipients whose average monthly utilization during a given term s is lower than 80% of the one-stage lower coverage limit. As explained in the summary statistics section, 80% is set here as the criterion rather than 50% to ensure sufficient statistical power because of the low number of LTCI recipients whose coverage falls over time. This set of modified low-demand recipients is narrowed further in the second step to those whose standardized care time in the following term $s+1$ is in the same or one-stage *lower* care-needs level compared with that of term s. The causal relation of interest is the same as equation 3.

$$\begin{aligned}\Delta Utilization_{it}^{s,s+1} = \alpha^c + \beta^c \Delta Coverage_i^{s,s+1} + f^c(Caretime_{is+1}) \\ + \gamma^c Caretime_{is} + X_{it}^{s,s+1}\eta^c + \varepsilon_{it}.\end{aligned} \tag{B.1}$$

The first-stage regression is

$$\begin{aligned}\Delta Coverage_i^{s,s+1} = \alpha_0^c + \beta_0^c \mathbb{1}\{Caretime_{is+1} < Cutoff\} + f_0^c(Caretime_{is+1}) \\ + \gamma_0^c Caretime_{is} + X_{it}^{s,s+1}\eta_0^c + \varepsilon_{it},\end{aligned} \tag{B.2}$$

where $\mathbb{1}\{Caretime_{is+1} < Cutoff\}$ is a dummy variable that takes a value of 1 if the standardized care time is less than a given cutoff value. Other notations and functional specifications are the same as those used for the estimation of coverage expansion. Consequently, β^c in equation B.1 indicates behavioral effects of coverage reduction on LTC utilization. As in the case of coverage expansion, I estimate the regression with high-demand recipients and with all recipients to make comparisons between responses resulting from behavioral biases and economic incentives.