

Causes and Consequences of Manipulation of Social Insurance Benefits ^{*}

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Abstract

Using administrative data of the public long-term care insurance (LTCI) in Japan, we document novel discontinuity and bunching in the distribution of health scores that determine benefit levels for LTCI. The distribution suggests that LTCI recipients tend to receive more generous benefits than they should because medical examiners manipulate recipients' health score. Our bunching estimation indicates that the manipulation increases monthly long-term care (LTC) expenditures by 5.7% on average. We also find that the vertical integration of examiners into LTC providers have little effects on manipulation, indicating that intrinsic psychological factors are more important than economic factors in the manipulation.

Keywords: Manipulation, social insurance, bunching, vertical integration, non-parametric estimation, shape restriction.

JEL Codes: C14, I13, I38.

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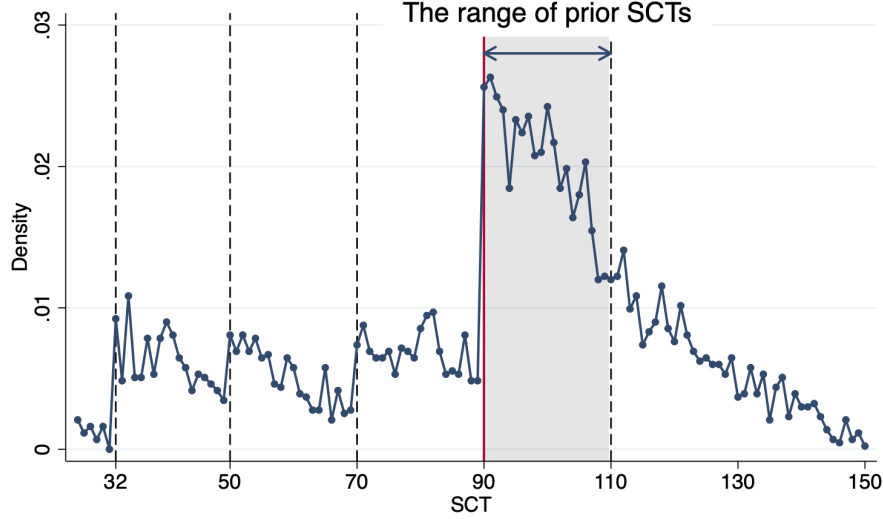
1 Introduction

Many social welfare programs rely on means testing to target individuals who require government assistance. For example, welfare programs in the United States such as Medicaid and SNAP use income, assets, and non-financial criteria to ascertain whether a certain individual is eligible for participation in a program. These means tests are high-stakes processes for disadvantaged people because their lives are strongly affected by eligibility for and generosity of welfare programs. Reliance on high-stakes means testing engenders concerns about the discretion in test results. A person in charge of testing might manipulate its results and discretionarily make certain individuals eligible for a program for political or economic gain.

In this paper, we explore causes and consequences of manipulation of means testing in the context of a large social insurance program: the public long-term care insurance (LTCI) in Japan. LTCI, a means-tested social insurance program, provides subsidies for long-term care (LTC) to elderly people with a disability. Because of rapid aging of the population, spending on LTCI has increased rapidly and the total cost amounted to 2.1% of Japanese GDP in 2019. A means test in LTCI is based on the degree of disability: Applicants for LTCI subsidies take health checkups and have a health index called standardized care time (SCT) calculated. Based on SCT, applicants are classified into one of seven care-needs levels, and the care-needs level determines LTCI benefits (insurance coverage generosity). Importantly, recipients must retake health checkups regularly. They are classified into a particular care-needs level each time based on a newly calculated SCT.

Using administrative data from a municipality near Tokyo, we first document large-scale manipulation of SCTs by showing clear discontinuity and bunching in the distribution of SCTs, conditional on the prior care-needs level. Specifically, the conditional distributions suggest that health checkup examiners manipulate SCTs to avoid assigning recipients to lower care-needs levels than the prior one. Figure 1 presents one example of conditional distributions indicating the existence of manipulation. It is a distribution of SCTs that is conditional on recipients whose prior SCT is within the indicated range. The care-needs level of these recipients will be lowered from the prior level if SCTs are lower than the red line threshold. The distribution has a discontinuity just at the threshold. The recipients below the threshold are far fewer than those above the threshold. The distributions conditional on

Figure 1: Bunching in the Conditional Distribution of SCTs



Notes: This figure presents a distribution of SCTs, conditional on recipients whose prior care-needs level was Care level 4 (prior SCTs were 90.0–109.9 min). The vertical red line represents a threshold determining whether recipients can maintain the same care-needs level and LTCI benefits as the prior term. The vertical dashed line represents other thresholds separating care-needs levels.

other care-needs levels exhibit the same property.

These distributions suggest that recipients who would otherwise have been considered under lower care-needs levels are classified into higher levels by manipulation of SCTs. Because it is unlikely that recipients can manipulate an SCT accurately by changing how their disability appears in a health checkup, health checkup examiners should be involved in the manipulation. Possible factors that might cause manipulation include the economic motivation of examiners who are vertically integrated with LTC providers. These examiners may have an incentive to keep recipients’ care-needs level high to maintain the profits of their integrated providers. Another possible reason is that examiners might be sympathetic to recipients and might want to maintain at least the LTC services that are currently available to them.

We then quantify the extent to which the manipulation of SCTs affects LTC expenditures (“manipulation effect”). Given that LTC expenditures tend to increase with care-needs levels, the manipulation is likely to increase LTC expenditures. For such quantification, it is necessary to recover the counterfactual distribution of SCTs without manipulation and to compare the observed and counterfactual expenditures. The empirical challenge is that manipulation

of SCTs covers a wide range and the conventional bunching approach based on a parametric interpolation may not be able to derive reliable counterfactual distribution. To address this difficulty, we develop a novel methodology to non-parametrically estimate counterfactual distribution. An important benefit of our method is that it can flexibly impose restrictions not only on the shape of distribution but also on the behavior of manipulation. For example, our method allows us to explicitly assume that health checkup examiner intentionally increase SCT, but not lower it. Figure 1 suggests that this assumption is reasonable and the restriction can be exploited to derive plausible counterfactual distribution. Our estimation shows that the manipulation of SCT increase LTC expenditure by 5% on average.

Furthermore, we explore the causes of manipulation of SCTs by comparing manipulation effects for different attributes of health checkup examiners and recipients. To investigate the influence of vertical relationship between the examiner and LTC provider, we separate sample whether the examiner is vertically integrated with provider and compare manipulation effects. We find that recipients' SCT are manipulated to the same extent regardless of the relationship between examiners and LTC providers, indicating that the economic motivation of examiners is not a main cause of manipulation. Similarly, we compare recipients with high LTC expenditures and those with low LTC expenditures and find that manipulation effects are almost the same for the two groups. The fact that recipients' SCT is manipulated regardless of the attributes of the examiners or recipients suggests that the examiners have a psychological resistance to lowering care-needs levels itself.

This paper primarily contributes to the literature analyzing discretionary decision-making in public policies. [Camacho and Conover \(2011\)](#) and [Brollo, Kaufmann, and La Ferrara \(2019\)](#) respectively examine the causes and consequences of discretionary enforcement of welfare program in Colombia and Brazil. They demonstrate that, in developing countries, politicians strategically manipulate the enforcement of welfare programs for political interests. In the health economics literature, the manipulation of patients' risk scores ("upcoding") by healthcare professionals is a well-studied issue. For example, [Geruso and Layton \(2020\)](#) show that upcoding by private insurers in Medicare Advantage generates significant excess public spending. The manipulation of test scores by school teachers has also received much attention. [Diamond and Persson \(2017\)](#) and [Dee, Dobbie, Jacob and Rockoff \(2019\)](#) use

bunching methods to detect score manipulation and quantify the effects of manipulation on children’s future outcomes. Aside from these specific issues, the manipulation of means-tested welfare programs in economically developed countries has rarely been analyzed. We demonstrate that the means testing of LTCI in Japan is manipulated extensively to avoid lowering recipients’ LTCI benefits by health checkup examiners. This result suggests that the manipulation of means testing can be prevalent, even in economically developed countries.

Our study also contributes to the growing literature on the bunching approach. In the past decade, the bunching approach developed by [Saez \(2010\)](#), [Chetty, Friedman, Olsen, and Pistaferri \(2011\)](#), and [Kleven and Waseem \(2013\)](#) has been applied to various topics. As the bunching approach has gained much popularity in many fields, some recent studies have proposed more general approaches to the bunching analysis based on partial identification and nonparametric estimation ([Diamond and Persson, 2017](#); [Blomquist, Newey, Kumar, and Liang, 2019](#); [Bertanha, McCallum, and Seegert, 2020](#); and [Goff, 2020](#)). Our methodological contribution is to make better use of the flexibility of the nonparametric estimation framework. We develop nonparametric estimation methods that are sufficiently flexible to incorporate behavioral restrictions as well as shape restrictions on counterfactual distribution. This feature indicate that our approach can be applied to various bunching analysis.

This paper proceeds as follows. Section 2 introduces the institutional background of LTCI in Japan. Section 3 documents bunching in the distribution of SCTs, which indicates the manipulation of LTCI benefits. Section 4 describes the administrative data and its summary statistics. Section 5 proposes partial identification and nonparametric estimation methods. Section 6 shows estimation results obtained under various set of restrictions. Section 7 concludes.

2 Institutional Background

Public long-term care insurance (LTCI) in Japan was launched in April 2000 to address growing needs for public long-term care (LTC) services. LTCI, a mandatory social insurance program, includes various LTC services subsidized by local government so that eligible recipients can choose and use necessary LTC services with moderate out-of-pocket payments. Recipients can choose to use home-based care or move into a nursing home. This study

specifically examines those who use home-based LTC services under LTCI. The annual total cost of LTCI amounted to 11.7 trillion JPY (117 billion USD, 2.1% of Japanese GDP) in 2019. Outlays for home-based care amount to half of that total cost.¹

The eligibility and generosity of LTCI benefits depend on the degree of disability of the recipient: recipients with more severe disability can receive more generous benefits. In the case of home-based care, the generosity of the LTCI benefits is mostly characterized by monthly coverage limits. Recipients can use LTC services with 10 or 20% of prices up until the coverage limit, after which they must pay the full price of the services.² Because of the drastic price differences within and outside of coverage limit, the generosity of coverage limits strongly influences LTC utilization (Takahashi, 2020).

In determining the generosity of the LTCI benefits, the health index called standardized care time (SCT) plays a key role. The SCT is calculated through face-to-face health checkups. It summarizes the degree of a recipient’s disability. Based on SCT, recipients are classified into a specific category that has corresponding benefit levels. Therefore, SCT determines the generosity of LTCI benefits and consequently affects a recipient’s LTC utilization. The following describes the basic institutional framework of LTCI.

Generosity of LTCI Benefits. LTCI has seven categories called care-needs levels according to the degree of disability. Care-needs levels consist of Support level 1 and 2, and Care level 1–5 in ascending order of the degree of disability. These categories define available services and coverage limits. The broad categories of the Support level and Care level define the LTC services available to recipients. Recipients who are classified as Support level can only use services particularly addressing preventive care, whereas those classified as Care level are allowed to use various usual LTC services.

Each care-needs level within the broad categories defines the monthly coverage limits. It is noteworthy that recipients who have a severe disability are presumed to be entitled to more generous coverage. Table 1 presents the coverage limit for each care-needs level expressed as

¹For simplicity, we use an exchange rate of 100 JPY = 1 USD throughout this paper.

²The 20% coinsurance, introduced in 2015, applies to people with a total annual income of more than 1.6 million JPY (16K USD), and that of first-insured family members is more than 3.46 million JPY (34.6K USD), or 2.8 million JPY (28K USD) for a single-person household).

Table 1: Monthly Coverage Limits for Each Care-needs Level

Care-needs level	SCT	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

Table 2: Category of Assistance and Range of Time Length

Category of assistance	Range of time length (min)
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
SCT	10.6–230.6

a total unit value for LTC services. One unit is approximately 10 JPY or about 0.1 USD. As Table 1 shows, recipients with more severe disabilities have more generous coverage limits available to them. Applicants with SCTs between 32 and 49.9 min are classified into either Support level 2 or Care level 1. This allocation procedure draws on specific items of SCT representing the applicants’ cognitive ability and variation in health status.³

Care-needs Certification. As described briefly above, SCT (health index of disability) plays a deterministic role in classifying recipients into a specific care-needs level. It is calculated through detailed health checkups called care-needs certification. People who want to use LTC services under the LTCI must apply to the local government and take health checkups.

Care-needs certification is based on a nationally standardized face-to-face survey conducted by a trained examiner (LTC examiner). LTC examiners are mainly municipal employees or recipients’ care managers.⁴ In care-needs certification, the examiner first checks 74 items about the applicant’s physical and mental conditions related to LTC. Based on the health checkup, a special formula is used to generate “hypothetical care times” for eight

³Recipients are sorted 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) It is likely that the physical and mental condition of the recipient is going to worsen rapidly.

⁴According 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.

categories of assistance. Table 2 lists the possible time ranges for each category. The sum of these care times is SCT, which represents the degree of disability of the applicant. The longer the SCT is, the more likely the applicant is to have a severe disability. Applicants are assigned to a corresponding care-needs level based on the calculated SCT. Table 1 presents a range of SCT and a corresponding care-needs level. Although applicants can be reassigned to another care-needs level for special health reasons, care-needs levels (and corresponding generosity of LTCI benefits) are mostly determined by SCT.

An important feature of LTCI is that recipients must take care-needs certification regularly to accommodate changes in health status over time. Therefore, for each certification, recipients are reclassified into a different care-needs level 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 at the beginning of each term to continue using LTCI services. Hereafter, we use “certification term” or “term” to represent each valid term of the care-needs certification.

Long-Term Care Utilization. Given a coverage limit and available services determined by SCT, recipients prepare a monthly usage plan (care plan) for LTC services. They usually create a care plan assisted by a care manager, which allows a choice of LTC services from widely various options. Consequently, LTC utilization is a joint decision involving a recipient, family member, and care manager.

The care-needs level to which recipients are assigned affects LTC utilization through multiple factors. Recipients have an incentive to keep their utilization below the coverage limit because of higher prices outside the coverage. If recipients are assigned to a lower care-needs level, then their utilization is constrained by a lower level of coverage limit. It is also possible that recipients might respond to a change in their care-needs level even if they are not constrained by coverage limits. For example, care managers propose a predetermined selection of services to recipients based on care-needs levels. Overall, recipients’ LTC utilization is affected strongly by the care-needs level, irrespective of the utilization level.

3 Motivating Facts

3.1 Discontinuity and Bunching in the Distribution of SCTs

A main dataset used for this study includes LTCI administrative data of care-needs certification obtained from a local government near Tokyo. This dataset includes each recipient’s SCT, which is used for classifying recipients to a specific care-needs level. The sample period of these data is June 2012 through March 2018.

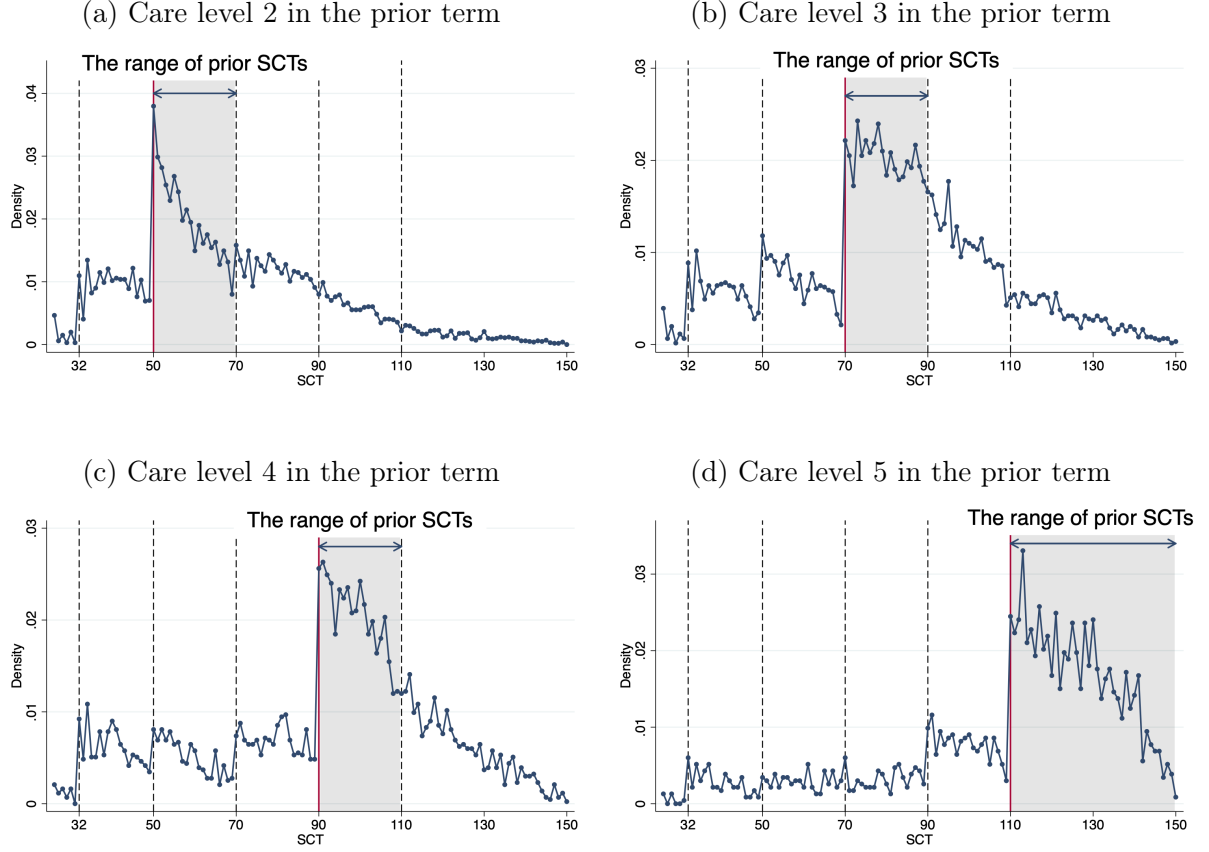
Here, we present notable reclassification patterns under the repeated care-needs certification. As described in the preceding section, recipients of the LTCI must take the care-needs certification at the beginning of each certification term. Figure 2 shows a distribution of recipients’ SCTs, *conditional on the prior care-needs level*.⁵ For instance, panel (a) is the distribution of SCTs for those whose prior care-needs level is Care level 2. All of these distributions have a sharp discontinuity at a certain level of SCT.

It is noteworthy that the position of discontinuity in these distributions corresponds exactly to a threshold determining whether recipients can maintain the same LTCI benefits as the prior term. In the case of those whose prior care-needs level was Care level 2, recipients’ care-needs levels (and LTCI benefits) are lowered if their SCT is below 50 min. Panel (a) in Figure 2 shows that the position of the discontinuity coincides with the threshold. The recipients below the threshold are far fewer than those above it. In contrast, no clear discontinuity exists at a threshold determining whether recipients can receive more generous benefits as the prior term (70 min in the case of panel (a)). The same explanation is applicable to other conditional distributions.

The discontinuity in the conditional distribution suggests that SCTs are manipulated to avoid classifying recipients into lower care-needs levels than the prior term. With many survey items, it is unlikely that recipients can manipulate SCT accurately by changing how their disability appears to LTC examiners. Consequently, LTC examiners who calculate SCTs should be involved in the manipulation. Because how the SCT is calculated from the survey items is public information and there is little external verification of how SCTs are assigned, some room exists for manipulation of SCTs by LTC examiners.

⁵In our sample, some recipients got the same hypothetical care times as the prior term in all categories of assistance shown in Table 2. We construct conditional distributions of SCTs without these recipients because they might not have gone through the proper process of care-needs certification.

Figure 2: Distribution of SCTs Conditional on the Prior Care-needs Level



Notes: This figure presents distributions of SCTs, conditional on prior care-needs levels. The vertical red line in each panel shows a threshold determining whether recipients can maintain the same care-needs level and LTCI benefits as the prior term. The vertical dashed lines represent other thresholds separating care-needs levels.

Actually, SCTs might be less likely to improve (that is, SCTs might be less likely to become lower) because of patterns of physical and mental deterioration of the capabilities of elderly people over time. Nevertheless, that trend alone should not generate discontinuity of SCT distribution. Appendix Figure A1 presents the distribution of changes in SCTs from the prior term to the current term, conditional on the prior care-needs level. These distributions have no discontinuity: the discontinuity in Figure 2 should be attributed to the manipulation of SCTs motivated by the thresholds.

Manipulation of SCTs is observed only for reclassification, conditional on the prior care-needs level. Appendix Figure A2 presents a distribution of SCTs calculated in the first certification (therefore no prior SCT). In contrast to the conditional distributions, distribu-

tion of the first SCTs has little discontinuity. Therefore, our analysis specifically examines the conditional distribution of SCTs resulting from reclassification of care-needs levels.

3.2 Potential Mechanisms of Manipulation

Some possible reasons can explain why LTC examiners manipulate SCTs to avoid lowering recipients' care-needs levels. The first is based on the integration of care managers into LTC providers. An important feature of care-needs certification is that care managers can conduct a certification as LTC examiners.⁶ It is also noteworthy that LTC providers are allowed to provide care management services to help create recipients' care plan. As a result, if a care manager who belongs to an LTC provider conducts care-needs certification, then the LTC examiner is integrated into the LTC provider. This organizational structure is similar to the vertical integration of diagnosis and treatment in the healthcare market.

The vertical integration may provide incentives for care managers to manipulate SCTs: For the integrated care managers, decreases in LTC utilization can engender decreases in profits of their integrated providers. Therefore, they might manipulate SCTs to guarantee that recipients can continue to use the LTC services they have been using as an LTC examiner. Even when recipient's care manager and LTC examiner are different people, the integrated care managers might use their influence on the examiners to prevent the recipients' care-needs level from being lowered.⁷

Second, the psychological factors LTC examiners face in care-needs certification may cause the manipulation of SCTs. LTC examiners might simply be sympathetic to recipients and might want to maintain at least those LTC services which are currently available to them. It is also possible that when recipients have to give up some LTC services they need because of lowering care-needs level, they and their family members may complain to examiners. LTC examiners or care managers might try to avoid such situation by manipulating SCTs. In such a case, manipulation of SCTs can occur without financial incentives such as vertical integration described above. We explore the mechanisms of manipulation by examining to

⁶Depending on whether it is a new application or a renewal application, the types of jobs that can be LTC examiners differ. In the case of new applications, the certification is conducted by a municipal employee or an LTC examiner who is a designated corporate employee. For renewals, which is a subject of this study, LTC providers and care managers approved by the government can also conduct certifications.

⁷In many cases, recipient's care manager is present at care-needs certification.

what extent the degree of manipulation varies depending on recipients' LTC expenditures and the integration of care managers into LTC providers.

4 Data

4.1 LTCI Administrative Data

For this study, we use LTCI administrative data from a local government near Tokyo. The first dataset is data on care-needs certification, which includes the SCT of each recipient. These data are available for each certification term. The available sample period is June 2012 through March 2018. It also includes a breakdown of how the SCT was calculated (that is, it provides a hypothetical care time for each category of assistance shown in Table 2) and other information related to care-needs certification such as the start and end dates of each certification term.

We also use LTCI claims data to observe recipients' LTC utilization. This dataset includes monthly information related to LTC utilization for all LTCI recipients in the city as well as demographic characteristics and eligibility status. The available sample period of these data is the same as the data related to care-needs certification. The claims data provide monthly information related to how much of each type of service each recipient used and what they paid for those services. The data include information related to the demographic characteristics of recipients, providing age and gender but no information related to income and family structure. Its eligibility information includes the care-needs level, start and end dates of each certification term, coinsurance rate, and special subsidy eligibility.

In addition, we use PAREA-Care II dataset published by Kokusai Kogyo, Co., Ltd. to gather information regarding care managers and LTC providers. PAREA is provider-level data and contains yearly information about what kind of care services are provided by each LTC provider. The LTCI claims data includes identification number for the LTC provider to which the recipient's care manager belongs. Therefore, we can observe the integration relation between recipients's care managers and LTC providers by linking PAREA data and the claims data.

The dataset for this analysis is constructed by linking the above datasets, which enables

us to associate recipients' LTC expenditures and their SCTs. Because our purpose is to analyze the manipulation of SCTs in reclassification, we specifically examine recipients who use home-based care, and recipients whose prior care-needs levels were Care levels 2–5. From this preliminary dataset, recipients of several types were excluded from the baseline analysis sample. First, recipients with a care-needs level that has been altered because of special health-related reasons have been omitted to maintain the relation between SCTs and care-needs levels. Second, recipients who got the same hypothetical care times as the prior term in all categories of assistance (Table 2) are omitted because they might not have gone through the proper process of recalculating their SCTs.⁸ The remaining recipients constitute a baseline sample.

4.2 Summary Statistics

We present summary statistics of the baseline sample in Table 3. Each column represents recipients' prior care-needs level. We define the LTC expenditures as the sum of out-of-pocket payments and payments from an insurer (municipality). The panel (A) presents the mean values of recipients' demographic characteristics and shows that they are almost identical among the prior care-needs levels. Because LTCI is a social insurance program mainly for the elderly population, recipients are old; the mean age of recipients is around 82 years old. More than half of recipients are women. The fraction of those who pay a higher coinsurance rate (20%) is about 10%.

The panel (B) presents recipient's monthly LTC expenditure and shows that the higher care-needs level in the prior term engenders higher LTC expenditure in the current term. LTC expenditures increase monotonically as prior care-needs levels become higher. We also present expenditures on two main LTC services, daycare and homecare. Daycare services allow recipients to go to the facility on day trips and receive services such as exercises, meals, and bathing. In the home care service, helpers visit the recipient's home and provide a variety of services to help the recipient in their daily life. The panel indicates that as prior care-needs level become higher, expenditures on homecare tend to increase rapidly.

To see how current care-needs levels affect LTC expenditure, Figure 3 presents the relation

⁸All figures presented in Section 3 were constructed without these recipients.

Table 3: Summary Statistics

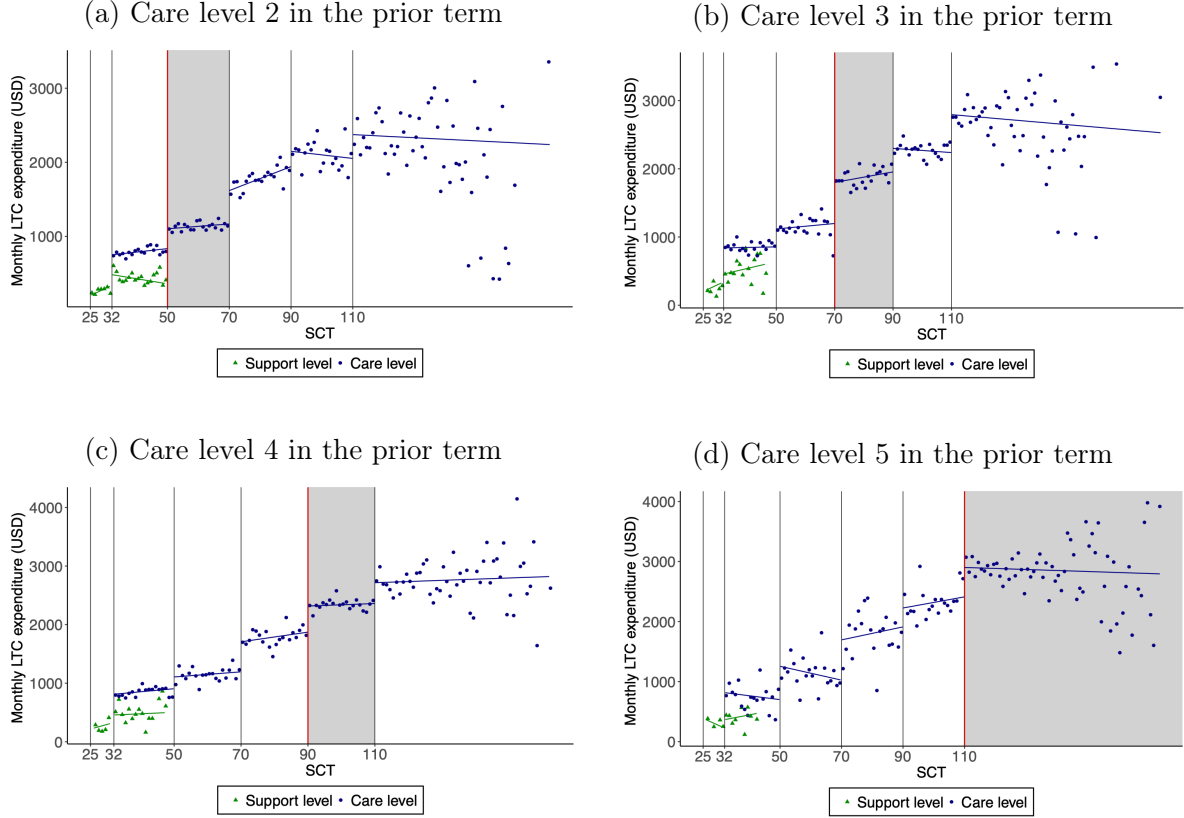
	Care level in the prior term				
	levels 2–5 (1)	level 2 (2)	level 3 (3)	level 4 (4)	level 5 (5)
(A) Demographics					
Age	82.6	82.8	82.7	82.4	81.6
Woman	0.62	0.61	0.61	0.63	0.63
20% coinsurance	0.10	0.11	0.11	0.10	0.09
(B) LTC expenditure					
Monthly expenditure (USD)	1,701	1,347	1,787	1,994	2,441
Daycare	617	547	715	620	653
Homecare	459	302	424	629	902
(C) Care managers					
VI Daycare	0.57	0.57	0.58	0.57	0.57
VI Homecare	0.65	0.64	0.65	0.70	0.68
Obs. (Recipient $\times$ Term)	23,014	10,138	6,117	4,349	2,410

Notes:

between SCTs and monthly LTC expenditures, conditional on the prior care-needs level. The grey area shows the range of prior SCTs. As this figure shows, LTC expenditures increase as current care-needs levels become higher and vary considerably at thresholds separating care-needs levels. Therefore the manipulation of SCTs that move recipients to higher care-needs levels can be expected to increase LTC expenditures.

As described in section 3.2, the manipulation of SCTs might be driven by the integration of care managers into LTC providers. The integration between care managers and LTC providers can be complex because there are differences in which types of LTC services are integrated among many services. For simplicity, we focus on the two main LTC services: daycare and homecare. Panel (C) presents the fraction of recipients whose care manager is vertically integrated (VI) with an LTC provider offering daycare or homecare services. The panel indicates that more than half of recipients are taken care of by care managers who belong to LTC providers offering daycare or homecare.

Figure 3: Monthly Expenditure on Long-Term Care Services



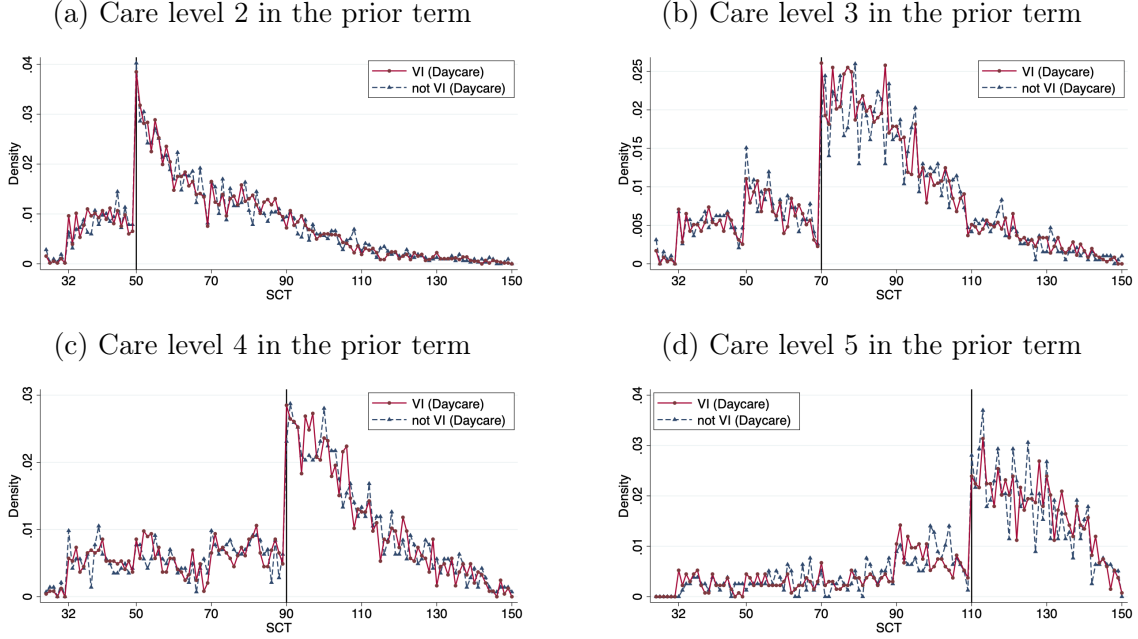
Notes: This figure presents the relation between SCT and LTC expenditure, conditional on the prior care-needs level. I divide SCT into 1 min-wide interval (bins). Each dot and triangle represents a local average of LTC expenditures within bins and a linear prediction is fitted on the plots for each care-needs level. The grey areas represent the range of the prior SCTs.

4.3 Distribution of SCTs by Recipients Types

To check the potential mechanisms of manipulation, we construct the conditional distribution of SCTs by recipients types. First, we divide recipients whether their care managers are vertically integrated with LTC providers offering daycare services (VI daycare) or not.⁹ The basic idea is that, if the vertical integration is the cause of manipulation, the bunching in the SCT distribution for integrated care managers should be greater than that for non-integrated care managers. Figure 4 compares the conditional distribution of SCTs of the two groups. The figure indicates that the conditional distributions of SCTs are almost identical

⁹The limitation of our dataset is that we do not observe whether recipient's care manager conducts care-needs certification. As explained in section 3.2, even when the care manager does not conduct certification, they might have the examiners manipulate SCTs.

Figure 4: Conditional Distribution by Vertical Integration (Daycare)

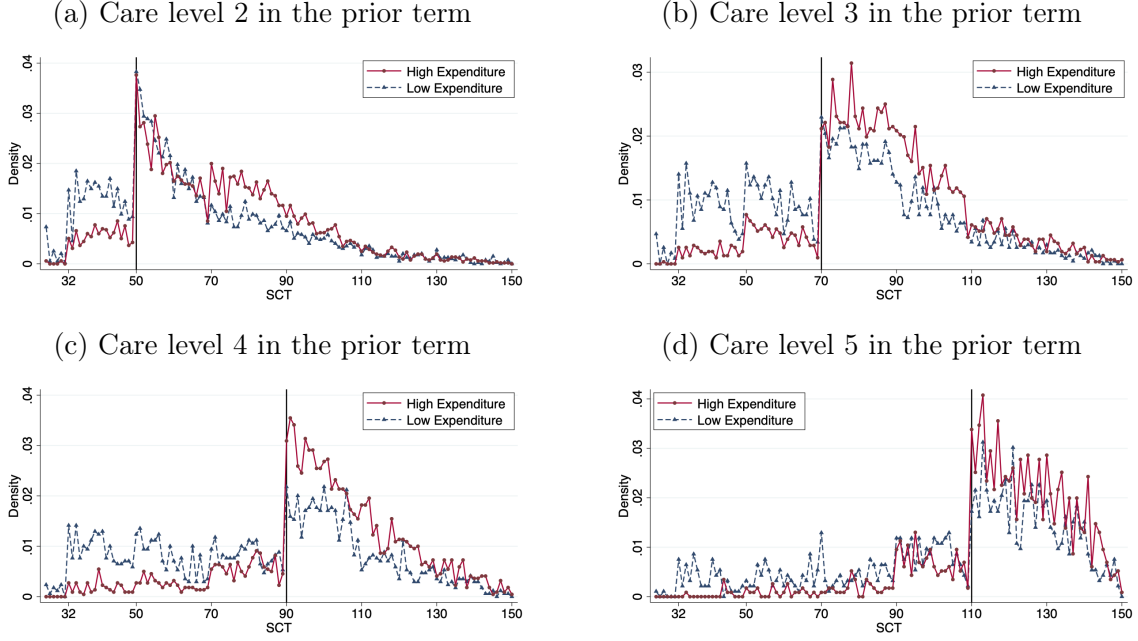


Notes:

between the two groups. Similarly, Appendix Figure A3 compares the distributions based on whether care managers are integrated into LTC providers offering homecare services or not. The figure also shows that the conditional distribution of SCTs is almost the same for the two groups. These result suggests that the integration of care managers into LTC providers is not the main cause of manipulation of SCTs.

Next, we check whether the conditional distribution of SCTs differs according to recipients' LTC utilization. Conditional on the prior care needs level, we divide recipients whether their LTC expenditure in the prior term was higher than the median or not. Figure 5 compares the distribution of SCTs for recipients with high expenditure and those with low expenditure. The figure shows the clear difference between the two groups: The discontinuity at the threshold and bunching in the distribution is larger for recipients with high expenditure compared with those with low expenditure. Appendix Figure A4 compares the distribution of SCTs of the two groups divided by whether recipients' prior SCT was above the median or not, conditional on the prior care-needs level. The figure indicates that recipients with low SCT are slightly more likely to be manipulated than those with high SCT,

Figure 5: Conditional Distribution by Expenditure



Notes:

but the difference is smaller than when divided by LTC expenditure.

Considering that the degree of manipulation is not affected by the vertical integration between care managers and LTC providers, it is plausible to interpret that LTC examiners manipulate SCTs because of psychological factors such as sympathy for recipients or psychological pressure from them rather than their economic interests. Figure 5 also suggests that LTC examiners manipulate SCT especially for recipients with high LTC expenditure. To check whether LTC examiners are more likely to manipulate SCTs for recipients with high LTC expenditure, it is necessary to construct counterfactual distribution of SCTs without manipulation. This is because, even if there is no manipulation of SCTs, recipients with high LTC expenditure may still to be assigned to higher care-needs levels than those with low LTC expenditure. In the following section, we propose a method to quantify the above results more rigorously.

5 Empirical Strategy

Our empirical goal is quantification of manipulation effects: the extent to which the manipulation of SCTs increases LTC expenditures. A central issue is how to construct a counterfactual distribution of SCTs without manipulation. Earlier literature on the bunching approach rely on the assumption of parametric functional forms for counterfactual distributions such as polynomials and construct them by interpolating the un-manipulable range of the observed distribution.

Counterfactual distributions constructed using the traditional approach might be unreliable when the manipulable range of distribution is wide. In such a case, as [Kleven \(2016\)](#) pointed out, researchers must interpolate over a wide range while relying on narrow un-manipulable ranges of distribution. Using ad-hoc parametric functional forms based on limited un-manipulable ranges raises doubts about the credibility of counterfactual distributions. Figure 2 shows that conditional distributions of SCTs present the same difficulty; SCTs can be manipulated, even if it is far below the threshold so that extensive interpolation is necessary to construct a counterfactual distribution. To address this issue, we propose nonparametric estimation methods to estimate the impact of manipulation on LTC expenditure. The key to our approach is the imposition of general restrictions on a counterfactual distribution without relying on parametric functional forms.

5.1 Target Parameters

Our analysis specifically examines the manipulation of SCTs, conditional on prior care-needs levels. Ideally, we should condition on prior SCTs rather than on care-needs levels, but such fine conditioning is insufficient to generate distributions that enable us to detect manipulation because of the resulting small sample size. Therefore, we use distributions of SCTs, conditional on the prior care-needs level to estimate manipulation effects. The following empirical method is applied to each of the conditional distributions.

We describe our empirical model using a conventional program evaluation framework. Conditioning on the prior care-needs level, then let X be an observed SCT which may be manipulated and let X^* be a counterfactual SCT without manipulation. Let us denote the care-needs levels corresponding to X and X^* as C and C^* , respectively. We define the

support of X and X^* as $\mathcal{X}$, and that of C and C^* as $\mathcal{C}$. Potential outcomes are indexed against potential care-needs levels $c \in \mathcal{C}$ and are denoted by $Y(c)$. Throughout this paper, we consider $Y(c)$ as the monthly LTC expenditure for recipients given care-needs level c .¹⁰ The observed outcome (expenditure) Y can be expressed as

$$Y = Y(C). \quad (1)$$

Then, the counterfactual expenditure Y^* can be written as

$$Y^* = Y(C^*). \quad (2)$$

The average treatment effect of manipulation is defined as $E[Y] - E[Y^*]$. Because $E[Y]$ is simply an average of observed expenditures, we focus on the identification of $\theta_0 \equiv E[Y^*]$.

To specify parameter θ_0 , we define the conditional expectation of counterfactual expenditures as $g(x) \equiv E[Y^*|X^* = x]$. Let f_X and f_{X^*} respectively denote PDFs of X and X^* . Then, θ_0 can be expressed as

$$\theta_0 = \int_{\mathcal{X}} g(x) f_{X^*}(x) dx. \quad (3)$$

If the value of SCT x provides care-needs level c , then we have $g(x) = E[Y(c)|X^* = x]$. The observed conditional expectation $E[Y|X = x]$ is equal to $E[Y(c)|X = x]$. Therefore, we can estimate $g(x)$ based on the observed expenditures by assuming the following condition:

$$E[Y(c)|X^* = x] = E[Y(c)|X = x]. \quad (4)$$

Under this equality condition, we can identify target parameter θ_0 if the counterfactual PDF $f_{X^*}(x)$ is identified for all x . We assume that equation (4) holds in the following discussion. In Section 5.5, we consider a case in which equation (4) does not hold, which implies that using observed expenditures engenders selection biases for $g(x)$ and θ_0 .

¹⁰LTC expenditure is the sum of out-of-pocket payments and payments from the insurer.

5.2 Restrictions on Counterfactual Distribution

In this section, we specify theoretical restrictions on the counterfactual distribution of SCTs. Without restrictions, the shape of counterfactual distribution can be too flexible to obtain meaningful information from observed distributions. We impose the following three restrictions on counterfactual distributions. It is noteworthy that we do not impose any parametric functional form.

R1: Un-manipulable Range. The first restriction is that a counterfactual PDF $f_{X^*}(x)$ coincides with an observed PDF $f_X(x)$ in un-manipulable ranges far from the threshold. Let $K \subset \mathcal{X}$ be un-manipulable ranges, whereas $K^C \equiv \mathcal{X} \setminus K$ is a manipulable range around the threshold. We assume that

$$f_{X^*}(x) = f_X(x) \quad \text{for } x \in K. \quad (5)$$

Most bunching literature relies on the same type of assumption. Because K^C is an interval, this restriction can be rewritten using cumulative distribution functions (CDFs):

$$F_{X^*}(x) = F_X(x) \quad \text{for } x \in K, \quad (6)$$

where $F_{X^*}(x)$ and $F_X(x)$ are CDFs corresponding respectively to $f_{X^*}(x)$ and $f_X(x)$.

R2: Log-concavity. To prevent counterfactual PDFs from having an implausible shape, we impose a shape restriction on them. Our second restriction is that $f_{X^*}(x)$ is a log-concave density. A PDF f is log-concave if $f(x) = \exp(h(x))$ with a concave function h . Any log-concave PDF is continuous and unimodal. It includes well-known univariate parametric families such as a normal distribution, a gamma distribution with shape parameter at least 1, and a $\text{beta}(\alpha, \beta)$ distribution with $\alpha, \beta \geq 1$. This restriction specifies a global shape of counterfactual PDFs that have no bunching around thresholds. The assumption of log-concavity is popular in economics. It has been applied in various fields (Cule, Samworth, and Stewart, 2010). In the bunching literature, Diamond and Persson (2017) impose log-

concavity on counterfactual PDFs of test scores.

R3: Stochastic Dominance. Furthermore, we also restrict how SCTs are manipulated. The third restriction is that the counterfactual distribution is first-order stochastically dominated by the observed distribution as:

$$F_{X^*}(x) \geq F_X(x) \quad \text{for all } x. \quad (7)$$

This restriction is equivalent to assuming that SCTs can be increased, but not decreased by manipulation. In other words, the true SCTs without manipulation might be lower than the observed value so that the counterfactual PDF should be shifted to the left of the observed one. This restriction implies that manipulation of SCTs must increase LTC expenditure if $g(x)$ is increasing monotonically with SCT x .

5.3 Estimation

We specify a set of PDFs satisfying R2 as

$$\mathcal{F} \equiv \left\{ f : f = \exp(h), \quad h(x) = \sum_{s=0}^S a_s b_s^S(x), \right. \\ \left. \begin{aligned} & a_s - 2a_{s+1} + a_{s+2} \leq 0 \text{ for } s = 0, 1, \dots, S-2, \\ & \text{and } \int f(x) dx = 1. \end{aligned} \right\}, \quad (8)$$

where b_s^S is the s -th Bernstein basis polynomial of degree S and $\{a_s\}_{s=0}^S$ parameterizes functions in $\mathcal{F}$.¹¹¹² From the property of the Bernstein polynomials, any function in $\mathcal{F}$ are log-concave (Wang and Ghosh, 2012; Diamond and Persson, 2017).

Given the set of functions $\mathcal{F}$, we estimate the counterfactual PDF as follows:

$$\hat{f}_{X^*} = \operatorname{argmin}_{f \in \mathcal{F}} \int_K \left| \hat{F}(x) - F_f(x) \right| dx + \int_{K^C} \left| \hat{F}(x) - F_f(x) \right|_+ dx, \quad (9)$$

¹¹The s -th Bernstein basis polynomial of degree S_n is defined as $b_s^{S_n}(x) \equiv \binom{S_n}{s} x^s (1-x)^{S_n-s}$. When using Bernstein basis polynomial, we rescale SCT to satisfy $x \in (0, 1)$.

¹²In estimation, we set $S = 7$ for log-concave densities.

where $F_f(x) \equiv \int_{-\infty}^x f(u)du$, $\hat{F}(x)$ is the empirical distribution function of X , and $|a|_+ \equiv \max\{0, a\}$. The first and second term can respectively be interpreted as a penalty for violating R1 and R3. Therefore, the estimator (9) minimizes a simple addition of two integrated loss functions regarding R1 and R3 under the restriction of R2.¹³

To estimate the manipulation effect, it is also necessary to specify the conditional expectation of counterfactual LTC expenditures, $g(x)$. We specify $g(x)$ as

$$\begin{aligned} g(x) = & \beta_0 + \beta_1^s \mathbf{1}\{x \geq 32, \text{ Support level}\} + \beta_1^c \mathbf{1}\{x \geq 32, \text{ Care level}\} \\ & + \beta_2 \mathbf{1}\{x \geq 50\} + \beta_3 \mathbf{1}\{x \geq 70\} + \beta_4 \mathbf{1}\{x \geq 90\} + \beta_5 \mathbf{1}\{x \geq 110\} \\ & + x \times \left\{ \gamma_0 + \gamma_1^s \mathbf{1}\{x \geq 32, \text{ Support level}\} + \gamma_1^c \mathbf{1}\{x \geq 32, \text{ Care level}\} \right. \\ & \quad \left. + \gamma_2 \mathbf{1}\{x \geq 50\} + \gamma_3 \mathbf{1}\{x \geq 70\} + \gamma_4 \mathbf{1}\{x \geq 90\} + \gamma_5 \mathbf{1}\{x \geq 110\} \right\}, \end{aligned} \tag{10}$$

where $\mathbf{1}\{\cdot\}$ is an indicator function that is equal to one if the statement in parenthesis is true, and zero otherwise. If SCTs are between 32.0 and 49.9, then recipients are assigned to either Support level 2 or Care level 1. The LTC expenditure is affected by the category to which they are assigned. We allocate recipients into one of these two categories based on the observed assignment probability if $x \in [32.0, 49.9]$. The specification of $g(x)$ is motivated by the observed patterns of LTC expenditures presented in Figure 3; LTC expenditures vary depending on both SCT x and care-needs levels. Therefore, the predicted value of $g(x)$ coincides with the linear prediction in Figure 3. We consider the issue of selection bias in $g(x)$ in Section 5.5.

Then, the estimator for counterfactual LTC expenditure is

$$\hat{\theta}_0 = \int \hat{g}(x) \hat{f}_{X^*}(x) dx, \tag{11}$$

where $\hat{g}(x)$ is a predicted value of regression model (10) and $\hat{f}_{X^*}$ is the estimated counter-

¹³In theory, it should be possible to determine the optimal criterion function based on a data-driven procedure (Carrasco and Florens, 2000). However, developing such a method can be quite challenging because of the ill-posed inverse problem and regularization issue. We leave this problem as a subject for future research.

Table 4: Manipulable Range of Distribution

	Care-needs level in the prior term			
	Care level 2 (1)	Care level 3 (2)	Care level 4 (3)	Care level 5 (4)
Manipulable Range	[32.0, 69.9]	[32.0, 89.9]	[32.0, 109.9]	[32.0, 129.9]
Threshold	50.0	70.0	90.0	110.0

Notes: This table presents manipulable ranges K^C . The threshold represents the level of SCT whether recipients can maintain the same care-needs level as the prior term.

factual PDF. The estimate for manipulation effects is the difference between observed and counterfactual LTC expenditure.

(Un-)Manipulable Range of Distribution. To implement the estimation presented above, we must determine the manipulable range of distribution, K^C . Figure 2 shows that when SCTs are smaller than the threshold, they can be manipulated to exceed the threshold value even if they are far from the threshold. This observation suggests that the start (left edge) of the manipulable range should be as distant from the threshold as possible. Therefore, we assume that SCTs in the lowest care-needs level (Support level 1) are un-manipulable and the starting point of K^C is 32 min (see Table 1). We also assume that SCTs are manipulated to maintain the prior care-needs level, which is equivalent to assuming that the “excess mass” of observed distribution is concentrated in the range of prior care-needs level. The first row in Table 4 summarizes the manipulable ranges K^C for the baseline analysis. In the case of Care level 5, we set the endpoint of K^C as 129.9 min so that the range of excess mass is the same as other care-needs levels. The un-manipulable range is determined automatically by $K = \mathcal{X} \setminus K^C$.

5.4 Identification Assumption

TBA.

5.5 Selection Biases in LTC Expenditures

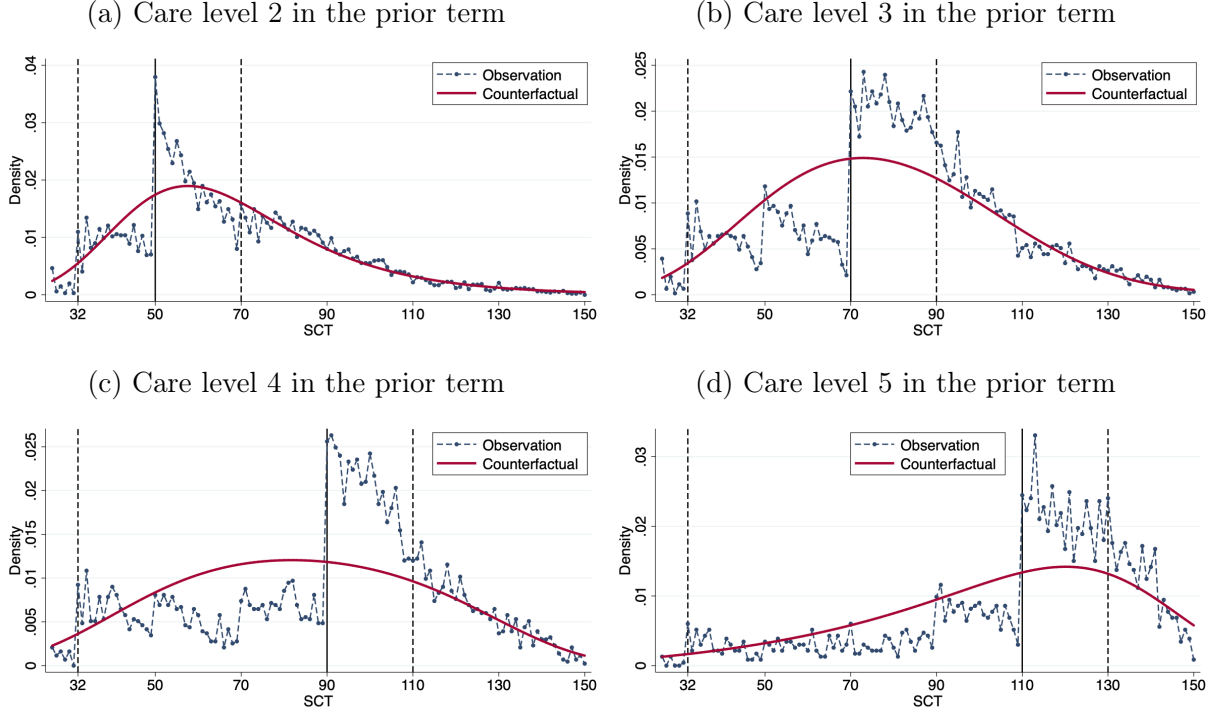
An important identification assumption is that the equation (4) holds. Specifically, the conditional expectation of counterfactual (*without* manipulation) LTC expenditures, $g(x)$, is specified using observed (*with* manipulation) expenditures. This assumption implies that the counterfactual LTC expenditures at a given SCT x are identical to the observed one. However, as shown in Figure 5, LTC examiners are more likely to manipulate SCTs for recipients with high LTC expenditures in the prior term. LTC expenditures are positively correlated overtime. Therefore, the manipulation of SCTs may increase the observed expenditures on the right side of the threshold and decreased them on the left side of the threshold when compared to the counterfactual expenditures without manipulation $g(x)$. If this is the case, assuming that the equation (4) holds, we ignore the potential selection bias in LTC expenditures.

To address this issue, we consider adjusting for $\hat{g}(x)$, the estimator for $g(x)$ specified using observed expenditures. Based on the discussion above, in the manipulable range K^C , using observed expenditures for $g(x)$ can engender over- (under-) estimation for counterfactual expenditure on the right (left) side of the threshold. To get closer to counterfactual expenditures, we adjust $\hat{g}(x)$ as

$$\hat{g}^s(x) = \begin{cases} \hat{g}(x) & \text{if } x \in K \\ \hat{g}(x) + \tau^l & \text{if } x \in K_l^C \\ \hat{g}(x) - \tau^r & \text{if } x \in K_r^C \end{cases} \quad (12)$$

where K_l^C and K_r^C respectively represent the left and right side of the manipulable range divided by the threshold. By setting $\tau^l > 0$ and $\tau^r > 0$, we raise (lower) $\hat{g}(x)$ on the left (right) side of the threshold in K^C . Appendix Figure A6 illustrates this adjustment. Replacing $\hat{g}(x)$ in (11) with $\hat{g}^s(x)$ is the adjusted estimator for θ_0 . Appendix B discusses that ignoring selection bias can engender underestimation of θ_0 . We examine how accounting for selection biases affects estimates for manipulation effects.

Figure 6: Observed and Counterfactual Distributions of SCTs (Baseline)



Notes: This figure presents observed and counterfactual distributions of SCTs using all baseline sample. The vertical line in each panel shows a threshold determining whether recipients can maintain the same care-needs level and LTCI benefits as the prior term. The vertical dashed lines represent the left and right ends of the manipulable range.

6 Results

6.1 Estimates for Manipulation Effects

We first illustrate counterfactual distributions of SCTs without manipulation. Figure 6 presents the observed (with manipulation) and counterfactual (without manipulation) distributions of SCTs using all baseline sample. The two dashed vertical lines represent the start and endpoint of the manipulable range. Using the estimation method above, the log-concave counterfactual PDF is constructed to be close to the observed PDF in the un-manipulable range, while being first-order stochastically dominated by the observed PDF. As shown in panel (c) and (d), even when the manipulable range is wide, our counterfactual distributions are reasonably bell-shaped and are in good agreement with the observed ones in the un-manipulable range. These distributions show that our nonparametric estimation method can generate valid counterfactual distribution in various cases.

Using counterfactual distributions, we can quantify to what extent the manipulation of SCTs affects the assignment of recipients' care-needs levels. Panel A in Table 5 presents the transition probability that recipient's SCT exceeds the threshold determining whether recipients can maintain the same care-needs level as the prior term, based on observed and counterfactual distributions. The first to fourth columns represent each prior care-needs level. The transition probabilities are higher for observation than for counterfactual, which indicates the manipulation to avoid assigning recipients to lower care-needs level than the prior one. The difference in transition probabilities between observation and counterfactual tend to be larger as the prior care-needs level get higher. This reflects the fact that the higher the prior care-needs level, the more room there is to lower care-needs level, and thus the impact of manipulation tend to be large. The fifth column presents the weighted average of transition probabilities presented in columns (1)–(4) to summarize the results. It shows that, on average, the manipulation of SCTs increases the probability of assigning recipients to the same or higher care-needs levels than the prior one by 11.5 percentage points (18.1%).

We then quantify to what extent the manipulation of SCTs increases LTC expenditures. Panel B in Table 5 presents the expected value of monthly LTC expenditures per recipient based on the observed and counterfactual distribution of SCTs. These expected values will be referred simply as “observed expenditures” and “counterfactual expenditures”, respectively. For counterfactual expenditures, we take into account potential selection biases using equation (12). Here, we focus on the discontinuous change in observed expenditures $\hat{g}(x)$ at the threshold that separates K_l^C and K_r^C . We set $\tau^l = \tau^r > 0$ to move $\hat{g}(x)$ by the same amount on both sides of the threshold and to reduce the differences in $\hat{g}(x)$ at the threshold. Specifically, we set τ^l and τ^r so that the difference in $\hat{g}^s(x)$ at the threshold is 50% of that of $\hat{g}(x)$. We present counterfactual LTC expenditures both with and without selection adjustment. Panel B shows that the observed expenditure is higher than the counterfactual expenditure irrespective of selection adjustment, indicating that the manipulation of SCTs indeed increases LTC expenditure.

Panel C presents the manipulation effects, the rate of change from counterfactual LTC expenditures to observed ones. Baseline estimates use counterfactual expenditures without selection adjustment, and selection adjusted estimates use those with selection adjustment.

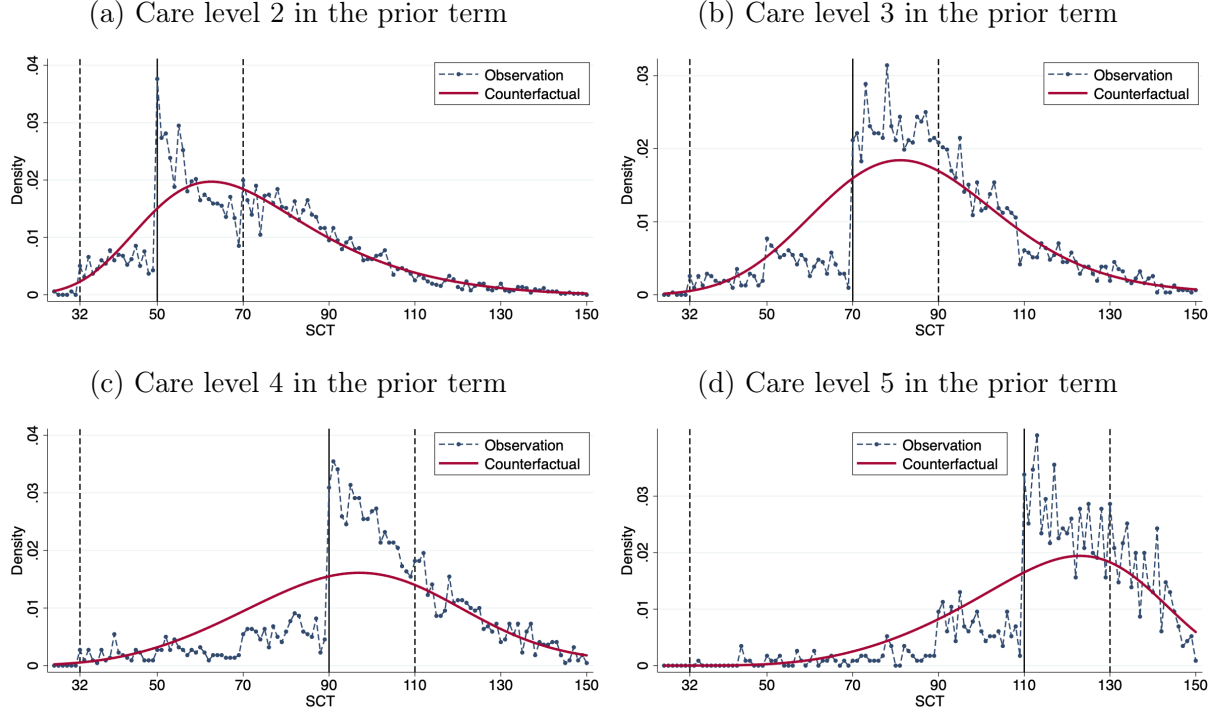
Table 5: Estimates for Manipulation Effects (Baseline Sample)

	Care-needs level in the prior term				Weighted average (5)
	Care level 2	Care level 3	Care level 4	Care level 5	
	(1)	(2)	(3)	(4)	
(A) The probability of SCT exceeding the threshold					
Observed	81.7%	74.5%	64.1%	66.9%	74.9%
Counterfactual	77.1%	60.6%	43.5%	48.4%	63.4%
(B) Monthly LTC expenditure (USD)					
Observed	1,343.2	1,782.9	1,988.0	2,426.0	1,692.8
Counterfactual	1,319.8	1,677.7	1,807.2	2,245.3	1,601.7
Counterfactual (Selection adj.)	1,307.4	1,690.5	1,843.5	2,280.0	1,610.1
(C) Manipulation effects					
Baseline	0.018 (0.005)	0.063 (0.006)	0.100 (0.008)	0.080 (0.008)	0.057
Selection adj.	0.027 (0.005)	0.055 (0.006)	0.073 (0.008)	0.064 (0.008)	0.051

Notes: This table presents the impact of manipulation on LTC expenditure using the baseline sample. Panel A presents the probability that recipient's SCT exceeds the threshold. The first to fourth columns represent each prior care-needs level. The fifth column represents the weighted average based on the number of observations for each prior care-needs level. Panel B shows the expected values of monthly LTC expenditure per recipient, conditional on the prior care-needs level. Panel C presents manipulation effects: the rate of change from counterfactual LTC expenditures to observed ones. The numbers in parentheses represent the standard error calculated by bootstrap procedure.

Standard error is calculated by bootstrapping method. Reflecting the transition probability presented in panel A, the manipulation effects vary greatly by the prior care-needs level. In the case of Care level 2, the manipulation increases LTC expenditure by only about 2%. This is because the fraction of recipients whose care-needs level become higher due to manipulation is limited. As the prior care-needs level is high, the manipulation effects tend to be large. Without selection adjustment, the manipulation increases LTC expenditures by 8–10% for recipients whose prior care-needs level is Care level 4 or 5. Even when potential selection biases are adjusted, the manipulation effects amounts to around 7% for these prior care-needs levels. The weighted average of manipulation effects indicates that the manipulation of SCTs increases LTC expenditures by more than 5% on average.

Figure 7: Observed and Counterfactual Distributions of SCTs (High Expenditures)



Notes: This figure presents observed and counterfactual distributions of SCTs using recipients with high LTC expenditure. The vertical line in each panel shows a threshold determining whether recipients can maintain the same care-needs level and LTCI benefits as the prior term. The vertical dashed lines represent the left and right ends of the manipulable range.

6.2 Estimates by LTC Expenditure Level

Figure 5 in section 4.3 shows that recipients with high LTC expenditures in the prior term are more likely to be assigned to the same or higher care-needs levels than those with low LTC expenditures. To examine whether LTC examiners are more likely to manipulate SCTs for recipients with high LTC expenditures, we divide recipients based on the median of prior LTC expenditures and estimate manipulation effects for both groups. Figure 7 presents the observed and counterfactual distributions of SCTs using recipients with high LTC expenditures. The observed and counterfactual distributions for those with low LTC expenditures are reported in Appendix Figure A7. Both figures show that our estimation method can construct reasonable counterfactual distribution of SCTs.

Table 6 summarize estimates for manipulation effects for the above two groups. Panel

A–C in Table 6 correspond to those in Table 5. Panel A shows that recipients with high LTC expenditures have a higher probability that their SCT exceeds the threshold than those with low LTC expenditures (86.2% vs. 75.5% on average). This clearly reflects the difference in observed distributions of SCTs between the two groups shown in Figure 5. More importantly, even if there is no manipulation, the probability of SCT exceeding the threshold is higher for recipients with high LTC expenditures than for those with low LTC expenditures (65.3% vs. 55.6% on average). The counterfactual distribution of SCTs without manipulation should reflect the distribution of recipients’ actual care needs. Therefore, the counterfactual distribution indicates that recipients with high LTC expenditures in the prior term are more likely to have higher care needs in the following term.

Based on the estimated counterfactual distributions, we find that LTC examiners manipulate SCTs equally for recipients with high LTC expenditures and those with low LTC expenditures. Panel A shows that the manipulation-induced increase in the probability of SCT exceeding the threshold is almost the same between the two groups on average ($\frac{86.2-65.3}{65.3} = 32.0\%$ vs. $\frac{75.5-55.6}{55.6} = 35.8\%$). Panel C presents manipulation effects, the rate of change from counterfactual LTC expenditures to observed ones, based on LTC expenditures presented in Panel B. The estimate for manipulation effects indicate that, on average, the manipulation of SCTs increase LTC expenditures by around 3% for both group. The manipulation effects for each care-needs level in the prior term are almost identical between recipients with high LTC expenditures and those with low LTC expenditures. Consequently, we conclude that even though the observed distributions are visibly different, manipulation effects do not depend on recipients’ LTC expenditures.

7 Conclusion

In this paper, we examine the economic consequences of manipulation of social insurance benefits in the context of public long-term care insurance (LTCI) in Japan. The generosity of LTCI benefits is determined by the care-needs levels. An LTC examiner categorizes recipients into a specific care-needs level based on health score (SCT). We first document the novel discontinuity and bunching in the distribution of SCTs, conditional on the prior care-needs level. The conditional distribution indicates that the LTC examiner, who calculates SCTs,

Table 6: Estimates for Manipulation Effects (By LTC Expenditure Level)

	Care-needs level in the prior term				Weighted average (5)
	Care level 2	Care level 3	Care level 4	Care level 5	
	(1)	(2)	(3)	(4)	
(A) The probability of SCT exceeding the threshold					
<u>Observed</u>					
High expenditure	89.6%	87.1%	80.3%	80.5%	86.2%
Low expenditure	75.0%	62.9%	49.9%	58.5%	75.5%
<u>Counterfactual</u>					
High expenditure	85.3%	75.1%	59.8%	63.6%	65.3%
Low expenditure	70.0%	50.4%	35.6%	44.0%	55.6%
(B) Monthly LTC expenditure (USD)					
<u>Observed</u>					
High expenditure	1,830.2	2,435.2	2,742.7	3,263.6	2,310.2
Low expenditure	944.6	1,260.2	1,400.1	1,902.6	1,214.7
<u>Counterfactual</u>					
High expenditure	1,803.9	2,353.1	2,619.4	3,144.4	2,241.2
Low expenditure	932.0	1,220.3	1,336.7	1,837.2	1,179.8
<u>Counterfactual (Selection adj.)</u>					
High expenditure	1,785.3	2,335.8	2,625.8	3,143.2	2,229.5
Low expenditure	929.4	1,229.1	1,364.4	1,843.6	1,186.9
(C) Manipulation effects					
<u>Baseline</u>					
High expenditure	0.015 (0.004)	0.035 (0.004)	0.047 (0.005)	0.038 (0.006)	0.028
Low expenditure	0.014 (0.009)	0.033 (0.008)	0.047 (0.008)	0.036 (0.009)	0.027
<u>Selection adj.</u>					
High expenditure	0.025 (0.004)	0.043 (0.004)	0.045 (0.005)	0.038 (0.006)	0.035
Low expenditure	0.018 (0.009)	0.048 (0.008)	0.062 (0.008)	0.032 (0.009)	0.022

Notes: This table presents estimates for the manipulation effects by LTC expenditure level. Panel A presents the probability that recipient's SCT exceeds the threshold. The first to fourth columns represent each prior care-needs level. The fifth column represents the weighted average based on the number of observations for each prior care-needs level. Panel B shows the expected values of monthly LTC expenditure per recipient, conditional on the prior care-needs level. Panel C presents manipulation effects: the rate of change from counterfactual LTC expenditures to observed ones.

manipulates SCTs, and avoids assigning recipients to a lower care-need level than the prior one. The higher care-needs level provides more generous LTCI benefits. Therefore, the manipulation is likely to increase LTC expenditures.

We quantify the manipulation effects by comparing LTC expenditure based on the observed SCT distribution and the counterfactual one. To construct a counterfactual distribution without manipulation, we develop a partial identification and nonparametric estimation method that does not rely on parametric functional forms. An important benefit of our method is that it allows for incorporation of flexible restrictions that can be tailored to specific applications. As the baseline restrictions, we assume that the counterfactual PDF is log-concave, and it is first-order stochastically dominated by the observed PDFs. We also examine how restrictions on counterfactual distribution affect bounds on manipulation effects by restricting how far SCTs can be manipulated and by generalizing the shape restriction.

Under the baseline restrictions, the manipulation of SCTs increases the probability of recipients' care-needs levels maintained above the prior one by at least 11.6 percentage points (18.3%). The lower bound of manipulation effects indicates that the manipulation of SCTs increases monthly LTC expenditure per recipient by at least 60.2 USD (3.7%). The upper bound is 227.9 USD (15.5%), which implies that the manipulation effects can amount to roughly four times more than the lower bound in monetary terms. The difference between lower bound and upper bound estimates suggests the importance of partial identification of counterfactual distributions when we need extensive interpolation to construct it. We also show that, using alternative restrictions, the estimates for lower bounds are robust to various restrictions. For this study, we analyze no specific cause of manipulation of social insurance benefits. Exploring circumstances under which manipulation is likely to occur can be a fruitful avenue for future research.

References

- Aliprantis, Charalambos D., and Kim C. Border.** 2006. "Infinite Dimensional Analysis: A Hitchhiker's Guide." *Springer*.
- Bertanha, Marinho, Andrew H. McCallum, and Mathan Seegert.** 2020. "Better Bunching, Nicer Notching." *Working Paper*.

- Best, Michael Carlos, Janes Cloyne, Ethan Ilzetzky, and Henrik Kleven.** 2018. “Estimating the Elasticity of Intertemporal Substitution Using Mortgage Notches.” *Review of Economic Studies*, 87(2), pp. 656–690.
- Blomquist, Soren, Whiteney K. Newey, Anil Kumar, and Che-Yuan Liang.** 2019. “On Bunching and Identification of the Taxable Income Elasticity.” *Working Paper*.
- Brollo, Fernanda, Katja Kaufmann, and Eliana La Ferrara.** 2019. “The Political Economy of Program Enforcement: Evidence from Brazil.” *Journal of European Economic Association*, 18(2), pp. 750–791.
- Camacho, Adriana and Emily Conover.** 2011. “Manipulation of Social Program Eligibility.” *American Economic Journal: Economic Policy*, 3(2), pp. 41–63.
- Carrasco, Marine and Jean-Pierre Florens.** 2000. “Generalization of GMM to a Continuum of Moment Conditions.” *Econometric Theory*, 16(6), pp. 797–834.
- Chen, Xiaohong.** 2007. “Chapter 76 Large Sample Sieve Estimation of Semi-Nonparametric Models.” *Handbook of Econometrics*, Vol. 6, Part 2, ed. by J. J. Heckman and E. E. Leamer. Elsevier, pp. 5549–5632.
- Chen, Zhao, Zhikuo Liu, Juan Carlos Suárez Serrato, and Daniel Yi Xu.** 2019. “Notching R&D Investment with Corporate Income Tax Cuts in China.” *Working Paper*.
- Chetty, Raj, John N. Friedman, and Emmanuel Saez.** 2013. “Using Differences in Knowledge Across Neighborhoods to Uncover the Impacts of the EITC on Earnings.” *American Economic Review*, 103(7), pp. 2683–2721.
- Chetty, Raj, John N. Friedman, Tore Olsen and Luigi Pistaferri.** 2011. “Adjustment Costs, Firm Responses, and Macro vs. Macro Labor Supply Elasticities: Evidence from Danish Tax Records.” *Quarterly Journal of Economics*, 126(2), pp. 749–804.
- Cule, Madeleine, Richard Samworth, and Michael Stewart.** 2010. “Maximum Likelihood Estimation of a Multi-Dimensional Log-Concave Density.” *Journal of the Royal Statistical Society*, 72(5), pp. 545–607.
- Dafny, Leemore S.** 2005. “How Do Hospitals Respond to Price Changes?.” *American Economic Review*, 95(5), pp.1525–1547.
- Dee, Thomas S., Will Dobbie, Brian A. Jacob, and Jonah Rockoff.** 2018. “The Causes and Consequences of Test Score Manipulation: Evidence from the New York Regents Examinations.” *American Economic Journal: Applied Economics*, 11(3), pp. 382–423.
- DeFusco, Anthony A. and Andrew Paciorek.** 2017. “The Interest Rate Elasticity of Mortgage Demand: Evidence from Bunching at the Conforming Loan Limit.” *American Economic Journal: Economic Policy*, 9(1), pp. 210–240.
- Diamond, Rebecca and Petra Persson.** 2017. “The Long-term Consequences of Teacher Discretion in Grading of High-stakes Tests.” *Working Paper*.
- Duflo, Esther, Michael Greenstone, Rohini Pande, and Nicholas Ryan.** 2018. “The Value of Regulatory Discretion: Estimates from Environmental Inspection in India.” *Econometrica*, 86(6), pp. 2123–2160.

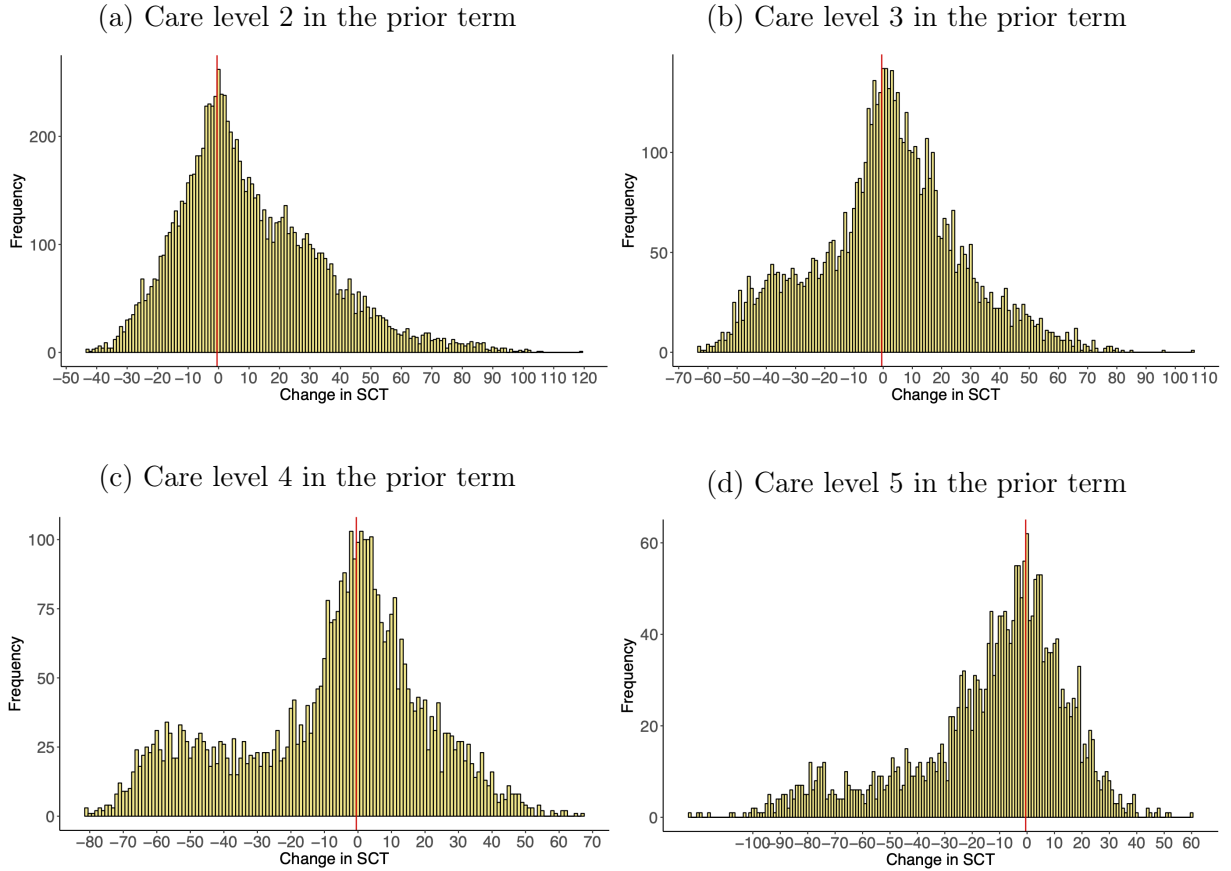
- Garicano, Luis, Claire Lelagré, and John Van Reenen.** 2016. “Firm Size Distortions and the Productivity Distribution: Evidence from France.” *American Economic Review*, 106(11), pp. 3439–3479.
- Gerard, Francois, Christoph Rothe, and Miikka Rokkanen.** 2020. “Bounds on Treatment Effects in Regression Discontinuity Designs with a Manipulated Running Variable.” *Quantitative Economics*, 11(3), pp. 839–870.
- Geruso, Michael and Timothy Layton.** 2020. “Upcoding: Evidence from Medicare on Squishy Risk Adjustment.” *Journal of Political Economy*, 128(3), pp.984–1026.
- Goff, Leonard.** 2020. “Treatment Effects in Bunching Designs: The Impact of the Federal Overtime Rule on Hours.” *Working Paper*.
- Ishihara, Takuya.** 2020. “Partial Identification of Discrete Instrumental Variable Models using Shape Restrictions.” *Working Paper*.
- Ishihara, Takuya and Masayuki Sawada.** 2020. “Manipulation-Robust Regression Discontinuity Design.” *Working Paper*.
- Kleven, Henrik J.** 2016. “Bunching.” *Annual Review of Economics*, 8, pp. 435–464.
- Kleven, Henrik J. and Mazhar Waseem.** 2013. “Using Notches to Uncover Optimization Frictions and Structural Elasticities: Theory and Evidence from Pakistan.” *Quarterly Journal of Economics*, 128(2), pp. 669–723.
- Manoli, Day and Andrea Weber.** 2016. “Nonparametric Evidence on the Effects of Financial Incentives on Retirement Decisions.” *American Economic Journal: Economic Policy*, 8(4), pp. 160–182.
- Manski, Charles.** 2003. “Partial Identification of Probability Distributions.” *Springer*.
- Marx, Benjamin M.** 2019. “Dynamic Bunching Estimation with Panel Data.” *Working Paper*.
- Mogstad, Magne, Andres Santos, and Alexander Torgovitsky.** 2018. “Using Instrumental Variables for Inference about Policy Relevant Treatment Parameters.” *Econometrica*, 86(5), pp. 1589–1619.
- Persson, Petra.** 2018. “Social Insurance and the Marriage Market.” *Journal of Political Economy*, 128(1), pp. 252–300.
- Rosenman, Evan and Karthik Rajkumar.** 2019. “Optimized Partial Identification Bounds for Regression Discontinuity Designs with Manipulation.” *Working Paper*.
- Saez, Emmanuel.** 2010. “Does Taxpayer Bunch at Kink Points?” *American Economic Journal, Economic Policy*, 2(3), pp. 180–212.
- Takahashi, Masaki.** 2020. “Behavioral Effects of Insurance Coverage and Health Consequences: Evidence from Long-Term Care.” *Working Paper*.
- Tebaldi, Pietro, Alexander Torgovitsky, and Hanbin Yang.** 2019. “Nonparametric Estimates of Demand in the California Health Insurance Exchange.” *Working Paper*.

- Torgovitsky, Alexander.** 2017. “Minimum Distance from Independence Estimation of Non-separable Instrumental Variables Models.” *Journal of Econometrics*, 199(1), pp.35–48
- Wang, Jiangdian and S.K. Ghosh.** 2012. “Shape Restricted Nonparametric Regression with Bernstein Polynomials.” *Computational Statistics & Data Analysis*, 56(9), pp. 2729–2741.

Online Appendix

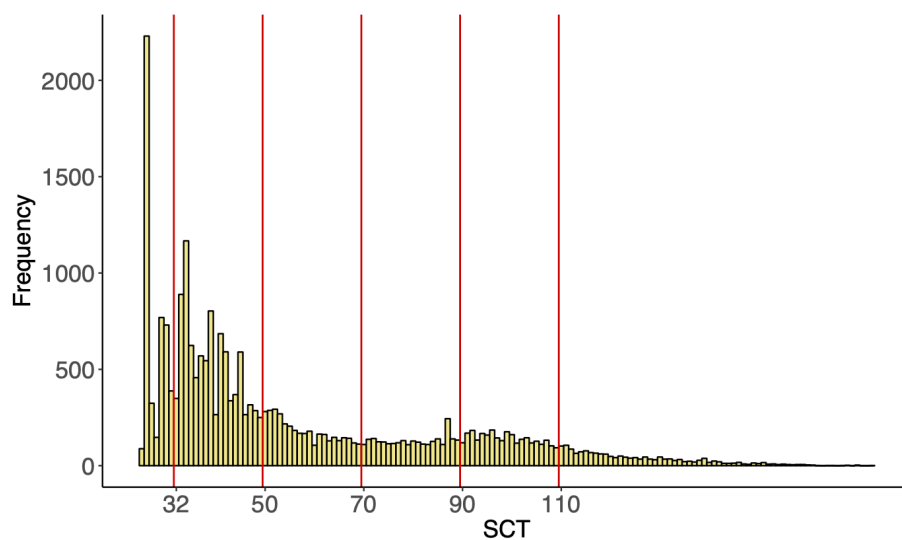
Appendix A: Figures and Tables

Figure A1: Distribution of Changes in SCTs



Notes: This figure presents distributions of differences between the current and prior SCTs, conditional on the prior care-needs levels.

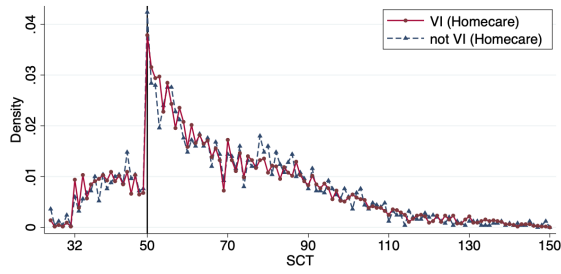
Figure A2: Distribution of SCTs (First Certification)



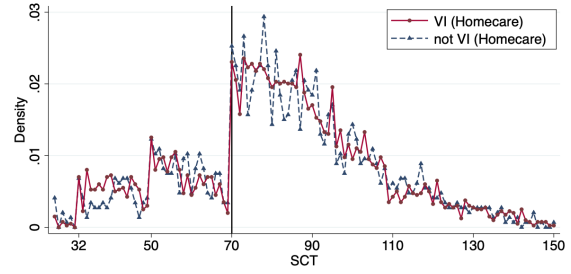
Notes: This figure presents the distribution of SCTs calculated in the first certification. The vertical red lines show thresholds separating care-needs levels.

Figure A3: Conditional Distribution by Vertical Integration (Homecare)

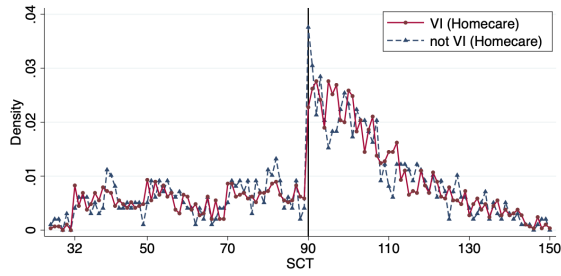
(a) Care level 2 in the prior term



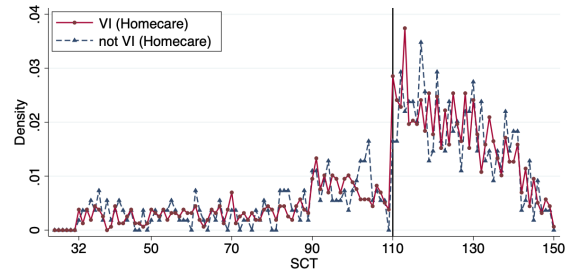
(b) Care level 3 in the prior term



(c) Care level 4 in the prior term

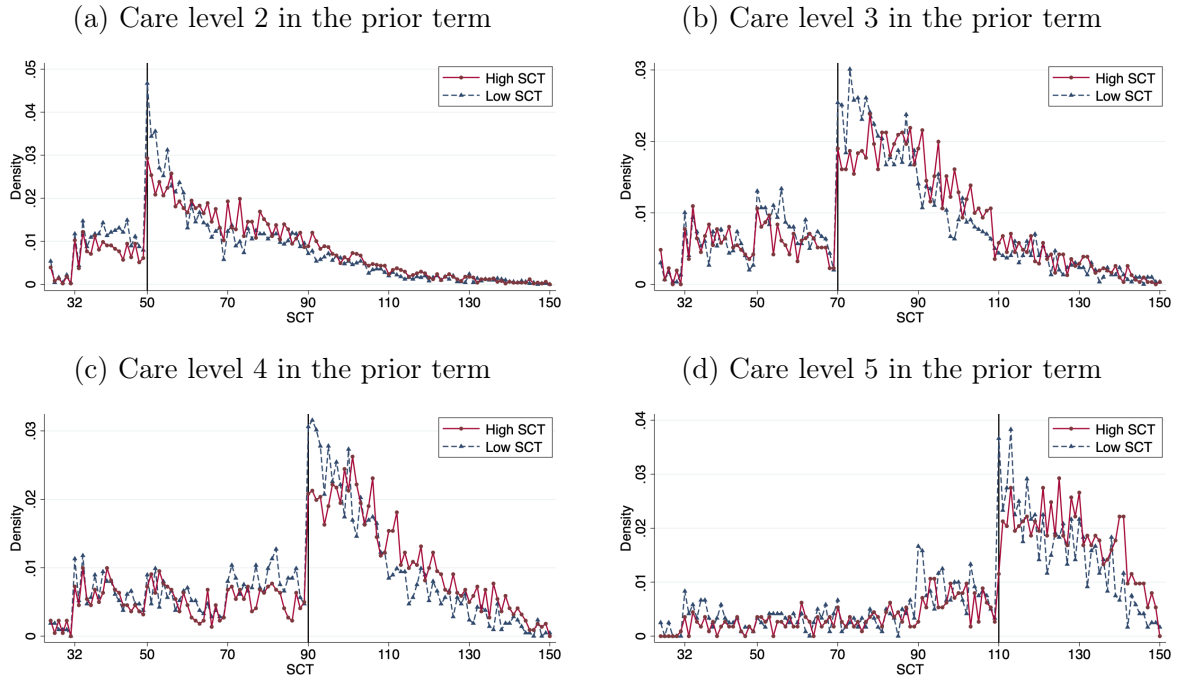


(d) Care level 5 in the prior term



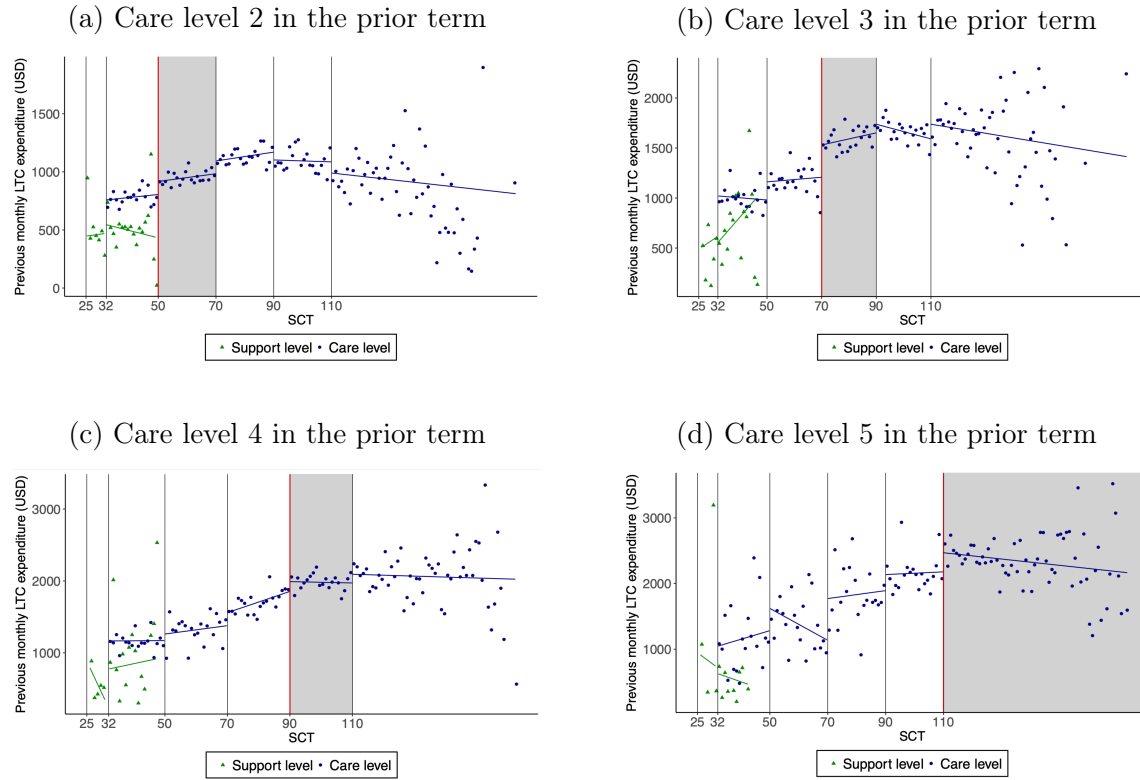
Notes:

Figure A4: Conditional Distribution by SCT



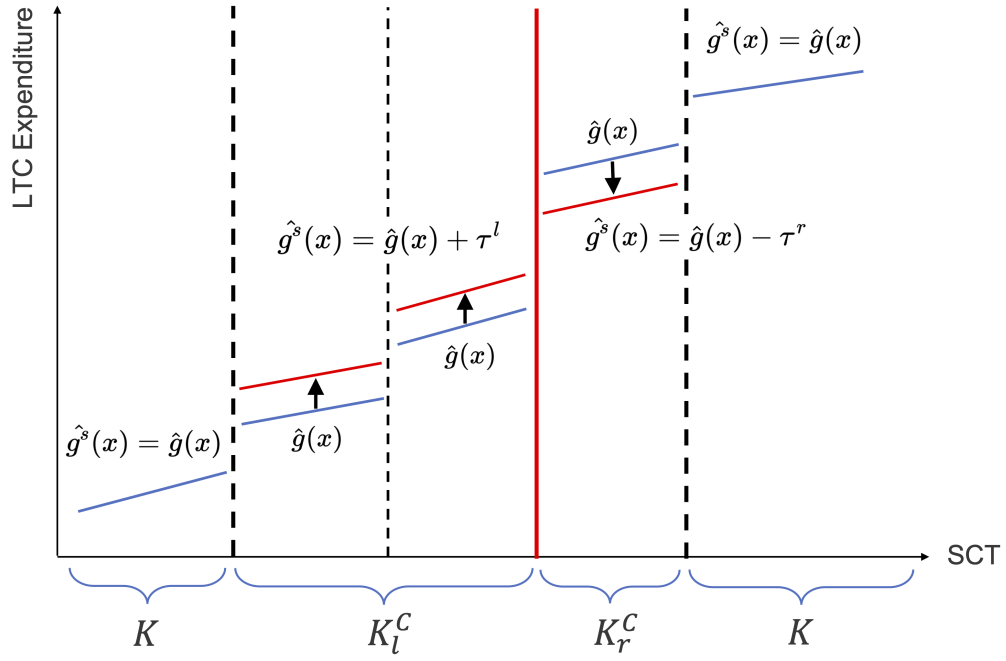
Notes:

Figure A5: Monthly Expenditure on LTC Services (Prior Term)



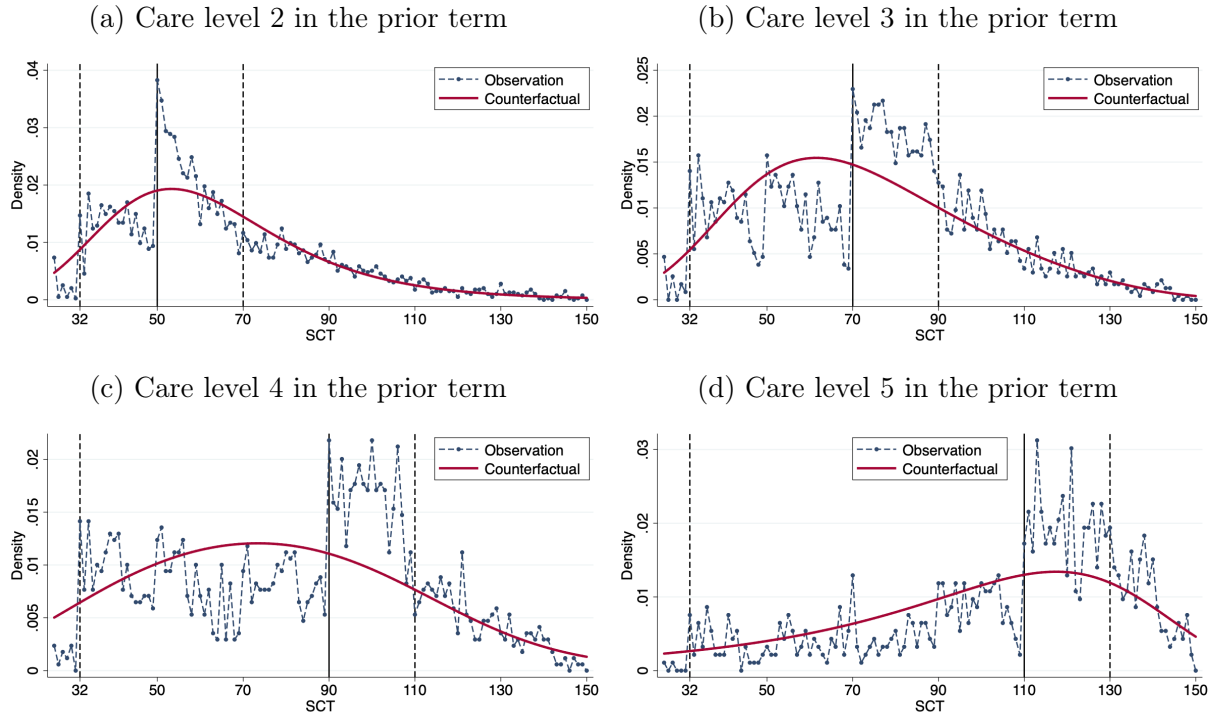
Notes: This figure presents the relation between SCTs and LTC expenditure during the prior term, conditional on the prior care-needs level. Here, SCT is divided into 1-min-wide interval (bins). Each dot and triangle represents a local average of LTC expenditures within bins. A linear prediction is fitted on the plots for each care-needs level. The grey areas represent the range of the prior SCTs.

Figure A6: Adjustment for Selection Biases



Notes: This figure illustrates the adjustment of $\hat{g}(x)$, which is specified as equation (12). K_l^C and K_r^C respectively represent the left and right side of manipulable range divided by the threshold. By setting $\tau^l > 1$ and $\tau^r < 1$, we raise (lower) $\hat{g}(x)$ on the left (right) side of the threshold in K^C .

Figure A7: Observed and Counterfactual Distributions of SCTs (Low Expenditures)



Notes: This figure presents observed and counterfactual distributions of SCTs using recipients with low LTC expenditure. The vertical line in each panel shows a threshold determining whether recipients can maintain the same care-needs level and LTCI benefits as the prior term. The vertical dashed lines represent the left and right ends of the manipulable range.

Table A1: Estimates for Manipulation Effects (VI with Daycare)

	Care-needs level in the prior term				Weighted average (5)
	Care level 2	Care level 3	Care level 4	Care level 5	
	(1)	(2)	(3)	(4)	
(A) Assigned to the same or higher care-needs levels					
<u>Observed</u>					
VI daycare	84.0%	76.7%	65.4%	67.6%	0%
non-VI daycare	84.4%	74.6%	65.5%	67.0%	0%
<u>Counterfactual</u>					
VI daycare	79.4%	62.2%	43.4%	51.4%	0%
non-VI daycare	79.2%	63.5%	45.3%	51.5%	0%
(B) Monthly LTC expenditure (USD)					
<u>(a) Observed</u>					
VI daycare	1,344.7	1,783.7	1,988.9	2,426.6	1,693.9
non-VI daycare	1,342.9	1,779.9	2,051.4	2,485.7	1,710.0
<u>(b) Counterfactual</u>					
VI daycare	1,351.4	1,710.5	1,817.2	0	0
non-VI daycare	1,319.8	1,699.2	1,869.2	2,349.8	1,629.9
<u>(c) Counterfactual (Selection adj.)</u>					
VI daycare	1,336.9	1,720.5	1,852.2	0	0
non-VI daycare	1,306.3	1,706.3	1,902.0	0	0
(C) Manipulation effects					
<u>Baseline ((a)-(b)/(b))</u>					
VI daycare	-0.005	0.043	0.094	0%	0%
	(SE)	(SE)	(SE)	(SE)	
non-VI daycare	0.017	0.048	0.097	0%	0%
	(SE)	(SE)	(SE)	(SE)	
<u>Selection adj. ((a)-(c)/(c))</u>					
VI daycare	0.006	0.037	0.074	0%	0%
	(SE)	(SE)	(SE)	(SE)	
non-VI daycare	0.028	0.043	0.079	0%	0%
	(SE)	(SE)	(SE)	(SE)	

Notes: This table presents the impact of manipulation on LTC expenditure using the baseline sample. Panel A presents the probability that recipients are assigned to the same or a higher care-needs levels than the prior one. The first to fourth columns represent each prior care-needs level. The fifth column represents the weighted average based on the number of observations for each prior care-needs level. Panel B shows the expected values of monthly LTC expenditure per recipient, conditional on the prior care-needs level. Panel C presents manipulation effects: the rate of change from counterfactual LTC expenditures to observed ones.

Table A2: Estimates for Manipulation Effects (VI with Homecare)

	Care-needs level in the prior term				Weighted average (5)
	Care level 2	Care level 3	Care level 4	Care level 5	
	(1)	(2)	(3)	(4)	
<u>(A) Assigned to the same or higher care-needs levels</u>					
<u>Observed</u>					
VI homecare	84.1%	75.8%	65.7%	67.7%	76.3%
non-VI homecare	84.2%	76.2%	64.7%	66.3%	76.6%
<u>Counterfactual</u>					
VI homecare	79.9%	69.7%	55.7%	58.0%	70.4%
non-VI homecare	79.4%	65.3%	46.2%	49.4%	66.3%
<u>(B) Monthly LTC expenditure (USD)</u>					
<u>(a) Observed</u>					
VI homecare	1,361.0	1,787.8	2,045.1	0	0
non-VI homecare	1,368.7	1,851.1	1,931.0	2,345.5	1,703.2
<u>(b) Counterfactual</u>					
VI homecare	1,338.7	1,767.8	2,014.3	0	0
non-VI homecare	1,346.3	1,755.9	1,774.7	2,1586	1619.3
<u>(c) Counterfactual (Selection adj.)</u>					
VI homecare	1,322.5	1,761.7	2,028.5	0	0
non-VI homecare	1,334.6	1,759.6	1,804.8	0	0
<u>(C) Manipulation effects</u>					
<u>Baseline ((a)-(b)/(b))</u>					
VI homecare	0%	0%	0%	0%	0%
	(SE)	(SE)	(SE)	(SE)	
non-VI homecare	0%	0%	0%	0%	0%
	(SE)	(SE)	(SE)	(SE)	
<u>Selection adj. ((a)-(c)/(c))</u>					
VI homecare	0%	0%	0%	0%	0%
	(SE)	(SE)	(SE)	(SE)	
non-VI homecare	0%	0%	0%	0%	0%
	(SE)	(SE)	(SE)	(SE)	

Notes: This table presents the impact of manipulation on LTC expenditure using the baseline sample. Panel A presents the probability that recipients are assigned to the same or a higher care-needs levels than the prior one. The first to fourth columns represent each prior care-needs level. The fifth column represents the weighted average based on the number of observations for each prior care-needs level. Panel B shows the expected values of monthly LTC expenditure per recipient, conditional on the prior care-needs level. Panel C presents manipulation effects: the rate of change from counterfactual LTC expenditures to observed ones.

Table A3: Estimates for Manipulation Effects (SCT)

	Care-needs level in the prior term				Weighted average (5)
	Care level 2	Care level 3	Care level 4	Care level 5	
	(1)	(2)	(3)	(4)	
<u>(A) Assigned to the same or higher care-needs levels</u>					
<u>Observed</u>					
High SCTs	0%	0%	0%	0%	0%
Low SCTs	0%	0%	0%	0%	0%
<u>Counterfactual</u>					
High SCTs	0%	0%	0%	0%	0%
Low SCTs	0%	0%	0%	0%	0%
<u>(B) Monthly LTC expenditure (USD)</u>					
<u>(a) Observed</u>					
High SCTs	0	0	0	0	0
Low SCTs	0	0	0	0	0
<u>(b) Counterfactual</u>					
High SCTs	0	0	0	0	0
Low SCTs	0	0	0	0	0
<u>(c) Counterfactual (Selection adj.)</u>					
High SCTs	0	0	0	0	0
Low SCTs	0	0	0	0	0
<u>(C) Manipulation effects</u>					
<u>Baseline ((a)-(b)/(b))</u>					
High SCTs	0%	0%	0%	0%	0%
	(SE)	(SE)	(SE)	(SE)	
Low SCTs	0%	0%	0%	0%	0%
	(SE)	(SE)	(SE)	(SE)	
<u>Selection adj. ((a)-(c)/(c))</u>					
High SCTs	0%	0%	0%	0%	0%
	(SE)	(SE)	(SE)	(SE)	
Low SCTs	0%	0%	0%	0%	0%
	(SE)	(SE)	(SE)	(SE)	

Notes: This table presents the impact of manipulation on LTC expenditure using the baseline sample. Panel A presents the probability that recipients are assigned to the same or a higher care-needs levels than the prior one. The first to fourth columns represent each prior care-needs level. The fifth column represents the weighted average based on the number of observations for each prior care-needs level. Panel B shows the expected values of monthly LTC expenditure per recipient, conditional on the prior care-needs level. Panel C presents manipulation effects: the rate of change from counterfactual LTC expenditures to observed ones.

Appendix B: Selection Biases

In this section, we consider the selection bias issue discussed in Section 5.5 and formally show that ignoring selection bias leads to underestimates for θ_0 . For simplicity, we assume that C is binary and determined by whether X is larger than the cut-off x_0 or not. That is,

$$\begin{aligned} C &= \mathbf{1}\{X \geq x_0\}, \\ C^* &= \mathbf{1}\{X^* \geq x_0\}. \end{aligned}$$

Then, we assume that the potential outcome $Y(c)$ can be expressed as follows:

$$Y(c) = h(c, X^*) + \epsilon, \quad E[\epsilon|X^*] = 0. \quad (\text{B.1})$$

This specification implies that X does not affect $Y(c)$ directly. In our setting, we can expect that a counterfactual SCT X^* represents recipient's health status and hence, the value of X only affect LTC expenditure through the care-needs level C conditional on X^* . Under the specification (B.1), $g(x)$ can be written as

$$g(x) \equiv E[Y^*|X^* = x] = h(0, x) \cdot \mathbf{1}\{x < x_0\} + h(1, x) \cdot \mathbf{1}\{x \geq x_0\}.$$

On the contrary, we have

$$\begin{aligned} E[Y|X = x] &= \{E[h(0, X^*)|X = x] + E[\epsilon|X = x]\} \cdot \mathbf{1}\{x < x_0\} \\ &\quad + \{E[h(1, X^*)|X = x] + E[\epsilon|X = x]\} \cdot \mathbf{1}\{x \geq x_0\}. \end{aligned}$$

Hence, if $h(c, x)$ is not equal to $E[h(c, X^*)|X = x] + E[\epsilon|X = x]$, then the assumption that $g(x)$ is identified using the conditional expectation of observed LTC expenditure may not be valid.

We compare $g(x) \equiv E[Y^*|X^* = x]$ and $E[Y|X = x]$ in this setting. Because we assume $X^* \leq X$, if $h(c, x)$ is increasing in x , then we obtain $E[h(c, X^*)|X = x] \leq h(c, x)$. We can expect that recipients with higher SCT have higher LTC expenditure. Hence, it is plausible that $h(c, x)$ is increasing in x . If LTC examiners keep recipients who will spend more on LTC

in the same care-needs level as the prior one, and assign those who will spend less on LTC to lower care-needs levels, then we may assume $E[\epsilon|X = x]$ is negative for $x < x_0$ and positive for $x \geq x_0$. This implies that $g(x) \equiv E[Y^*|X^* = x]$ is larger than the observed conditional expectation $E[Y|X = x]$ for $x < x_0$. If $h(c, x)$ is nearly flat or the difference between X^* and X are small, then the difference between $h(c, x)$ and $E[h(c, X^*)|X = x]$ becomes small. In this case, we can expect that $g(x)$ is smaller than $E[Y|X = x]$ for $x \geq x_0$.

Finally, we show that ignoring selection bias leads to underestimates for θ_0 . When using $E[Y|X = x]$ instead of $g(x)$, our estimand becomes $\tilde{\theta} \equiv \int E[Y|X = x]f_{X^*}(x)dx$. Then, we have

$$\begin{aligned}
\theta_0 - \tilde{\theta} &= \int \{E[Y^*|X^* = x] - E[Y|X = x]\} \cdot f_{X^*}(x)dx \\
&= \int_{-\infty}^{x_0} \{h(0, x) - E[h(0, X^*)|X = x] - E[\epsilon|X = x]\} \cdot f_{X^*}(x)dx \\
&\quad + \int_{x_0}^{+\infty} \{h(1, x) - E[h(1, X^*)|X = x] - E[\epsilon|X = x]\} \cdot f_{X^*}(x)dx \\
&\geq - \int E[\epsilon|X = x] \cdot f_{X^*}(x)dx = \int E[\epsilon|X = x] \cdot \{f_X(x) - f_{X^*}(x)\} dx,
\end{aligned}$$

where the last equality follows from $\int E[\epsilon|X = x] \cdot f_X(x)dx = E[\epsilon] = 0$. From the observed density of SCTs, we can expect $f_X(x) - f_{X^*}(x)$ is negative for $x < x_0$ and positive for $x \geq x_0$. Hence, ignoring selection bias leads to underestimates for θ_0 and overestimates for manipulation effects $E[Y] - \theta_0$.