Does decentralization work under declining local population? Evaluation of Japanese long-term care policy*

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We evaluate a decentralization policy for public long-term care insurance in Japan, where the aging-related population decline has created challenges for local authorities. The policy shifted the responsibility of setting the content and prices of covered care services from the central government to municipalities and deregulated staff qualification requirements to cut costs. Using a staggered difference-in-differences approach and nationally-representative individual-level data, we find a 2.8% reduction in expenditures and a 133% increase in worse care-need transitions post-policy. These results imply that the flexibility gained through decentralization is offset by a decline in care quality, particularly in resource-limited areas.

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1. Introduction

The rapid aging of populations worldwide has led several countries to anticipate population decline in the near future. In addition to Japan and China, which have already experienced such declines, United Nations (2019) predicted that 55 countries, including Germany, will face population reductions between 2019 and 2050. Furthermore, Bricker and Ibbitson (2019) presented several projections, with the most severe scenario predicting a global population decline beginning in 2050. Although the economic effects of aging have been extensively studied from various perspectives (Cutler *et al.*, 1990; Weil, 1997), the consequences of population decline have only recently begun to attract attention. Most existing studies focus on theoretical analyses of the relationship between population decline and macroeconomic growth (Jones, 2022; Maestas *et al.*, 2023). Applied research remains limited, reflecting the novelty of this phenomenon.

In this study, we examine the economic implication of population decline for regional economic policy, specifically evaluating decentralization policies in the context of shrinking populations. Decentralization, which has generally yielded positive outcomes in developed countries, raises important questions about its effectiveness under the circumstances of population decline. In public services provision, the discussion centers on the appropriate level of government to manage operations. When central government or other upper-level authorities handle such responsibilities, decentralization can potentially enable more flexible operations by transferring control to lower-level authorities. According to Tiebout (1956) and Oates (1972), local authorities, being closer to their constituents, can leverage local human resources to implement policies better aligned with regional demand and supply conditions. Reviewing empirical studies, Martínez-Vázquez *et al.* (2017) reported that decentralization in health policies often improved outcomes and decreased regional inequality by stimulating policy participation, although it tended to involve higher costs than centralized approaches.

However, the potential disadvantages of decentralization become apparent in the context of population decline. Some studies highlight the loss of economies of scale economy that centralized systems enjoy (Alesina and Spolaore, 2005; OECD, 2019). When disparities exist among local authorities, smaller authorities are more likely to face resource constraints (Prud'Homme, 1995). Under such circumstances, decentralization can even exacerbate regional inequality (Rodríguez-Pose and Ezcurra, 2010, 2011).

In this study, we analyze a decentralization policy in Japan, a country experiencing drastic demographic transitions (Feyrer *et al.*, 2008). Since 2008, Japan has experienced a natural population decline due to a low birth rate and high mortality rate. While other countries face similar trends, their declines are often driven by international migration outflows (United Nations, 2019). By contrast, Japan has relatively low levels of international migration, either from or to the country (McAuliffe and Oucho, 2024). Instead, internal migration from rural to urban areas, particularly among the working-age population has contributed to the depopulation of rural areas, leading to a reduction in local resources necessary for implementing decentralization policies. Moreover, pre-existing regional disparities in the size and capacity of local authorities have worsened due to this demographic shift.

We evaluate a recent top-down decentralization policy in long-term care, which has started under the local population decline. The Japanese government established the Long-Term Care Insurance (LTCI) system in 2000 as a mandatory social insurance to cover long-term care expenditures. Between 2015 and 2017, Municipality Unified Operation (MUO, *shichoson sougou jigyo*) amended LTCI by decentralizing the responsibility for setting the content and prices of care services covered by LTCI from the central government to municipalities, the smallest units of local governance. To meet cost-saving targets, the policy also encouraged municipalities to relax staff requirements and allow unqualified personnel to provide non-technical services, which were deemed less expertise-dependent.

For empirical evaluations of MUO, we analyze a large dataset for nationally-representative individuals derived from administrative records for LTCI claims and care needs. Outcome variables are selected to represent both the inputs and outputs of the MUO. Inputs are analyzed through extensive and intensive margins, while outputs are assessed via transitions in care needs, which reflect user well-being. Monthly panel data is used for input analysis, whereas cross-sectional data is employed to evaluate care-need transitions.

As municipalities are allowed to set the month to activate the MUO, the timing of its adoption varies. This non-random adoption schedule could introduce a correlation between the timing and policy outcomes, particularly if municipalities expecting better outcomes implemented the policy earlier. Recent studies (Goodman-Bacon, 2021; Baker *et al.*, 2022) have shown that in such cases, the simple difference-in-differences (DID) approach can yield biased estimates of the average treatment effects on treated (ATT). Diagnostic methods proposed by Jakiela (2021) revealed potential bias in our dataset. To address this, we utilized the staggered DID approach, primarily employing the method of Callaway and Sant'Anna (2021), which accommodates both panel and cross-sectional data. For robustness checks, we also used alternative staggered DID estimation methods of Sun and Abraham (2021) and De Chaisemartin and d'Haultfoeuille (2024).

Our empirical results suggest that the policy did not significantly increase service usage despite entry deregulation and the introduction of new services. Rather, we find a 2.8% decrease in individual-level expenditures and a 133% increase in worse care-need transitions. These findings imply that although MUO reduces service costs through deregulation, it has failed to maintain the effectiveness of services, thereby negating the operational flexibility advantage of decentralization with a decline in care quality. Additionally, our results indicate that MUO exacerbated regional inequalities in access to care services, as small municipalities with limited resources struggled to benefit from decentralization. These findings suggest that designing an efficient decentralization mechanism under local population decline remains challenging. Although the government currently plans to extend MUO to individuals with more severe care needs in the near future, such extensions require careful evaluation of policy effects.

This study contributes to several strands of literature. In the health care sector, decentralization has been widely adopted (Costa-Font and Greer, 2016). Numerous studies have utilized the DID approach for policy evaluation. Jiménez-Rubio and García-Gómez (2017) analyzed decentralization in Spain and found mortality rates decreased when both political and fiscal decentralization were achieved. Similarly, Di Novi *et al.* (2019) investigated the decentralization of flu vaccination in Italy and reported reduced inequality in wealthier regions. Our findings align more closely with those of Toth (2014), who observed that health care decentralization widened the gap between North and South Italy due to resource disparities in the Southern regions.

In the context of long-term care policy, ongoing debate surrounds the choice of the appropriate level of local authority for policy implementation (Häkkinen, 2005; Fernandez and Forder, 2015). Among countries with LTCI systems, Germany assigns responsibility to the states, the first-order administrative divisions (Rothgang, 2010), whereas South Korea operates with a single national-level insurer (Kim and Kwon, 2021). The Netherlands represents an exception, as its LTCI amendment in 2017 decentralized responsibility for service provision from the central government to municipalities (Alders and Schut, 2022). Thus, Japan's LTCI already featured decentralization by international standards, with MUO pushing these efforts even further. Moreover, Japan's long-term care policy under local population shrinkage offers valuable insights for China, which faces similar challenges due to internal migration from rural to urban areas (Lei *et al.*, 2022).

This study also adds to the literature on staffing regulations in health economics. Extensive research exists on minimum staffing requirements in US nursing homes (Grabowski and Bowblis, 2023). Although some studies identified distortions in incentives (Bowblis and Lucas, 2012; Chen and Grabowski, 2015), others demonstrated positive effects of staffing regulation on health outcomes (Zhang and Grabowski, 2004; Konetzka *et al.*, 2008; Lin, 2014; Brunt, 2023). Conversely, an emerging body of literature explores the deregulation of occupational requirements for health professionals such as nurse practitioners (Kleiner *et al.*, 2016; McMichael, 2023). These studies generally show that deregulation improves access to care at lower costs and has positive or neutral impacts on health outcomes. In short, staffing deregulations can have either positive or negative effects on health outcomes, depending on the context. In the case of our study, the deregulation policy was aimed primarily at cost reduction rather than efficiency, and our findings demonstrate that it leads to lower-quality care.

2. Background

2.1. Local population decline in Japan

Japan has been experiencing natural population decline due to low birth rate and high death rate[1]. According to Vital Statistics[2], Japan's total population peaked in 2008 and has been decreasing ever since. Unlike countries with active international immigration outflows, such as those in East Europe, which have experienced urban population shrinkage, Japan's population decline is not influenced by major international migration (Haase *et al.*, 2016). Instead, internal migration from rural to urban areas, particularly among the working-age population, has been a driving factor in Japan's population reduction (Higa *et al.*, 2019). This trend has resulted in rural population shrinkage.

Japan's population decline is not only persistent but is also expected to intensify, as reflected in national projections. The National Institute of Population and Social Security Research continuously provides estimations and forecasts on population transitions. According to its 2023 estimates[3], between 2015 and 2020, 81.9% of municipalities, except for large cities and the Okinawan island area, experienced population decreases. Their long-term forecasts indicate that even these exceptions will face population shrinkage in the near future. At the prefecture level, which is the second largest administrative unit after the central government, 46 prefectures, except Tokyo, are projected to experience population declines between 2020 and 2025. Moreover, the magnitude of these decreases is expected to intensify at least up to 2050, the last year of their forecast period.

Another notable characteristic of Japan's population is the significant disparity in the size of its municipalities. To strengthen municipal autonomy, the central government

[1]See Coulmas (2007) for more details on demographic trends in Japan

[2]Source: `https://www.mhlw.go.jp/toukei/list/81-1a.html` (in Japanese)

[3]Source: Population forecast of Japan: 2023 estimates by National Institute of Population and Social Security Research (`https://www.ipss.go.jp/pp-shicyoson/j/shicyoson23/t-page.asp`, in Japanese).

implemented the Heisei mergers in the early 2000s, encouraging municipal consolidation. Consequently, the number of municipalities decreased from 3,229 in 1999 to 1,821 in 2006. However, as Weese (2015) demonstrated, many municipalities engaged in strategic behavior of not pursuing social optimization. This led to a greater-than-expected number of post-merger municipalities, perpetuating regional disparities. According to the 2015 Census, the average municipal population was 73,935, but the extremes were stark: Yokohama had 3,724,844 residents while Aogashima had only 178. Consequent to the local population decline, these regional disparities in the size of local authorities, which existed even before the decline, have only widened.

As part of efforts to enhance the efficiency of local authorities, the central government introduced several reforms alongside the Heisei mergers. Between 2005 and 2009, the central government compelled municipalities to adopt the Condensed Reform Plan (*shuuchuu kaikaku plan*), which mandated a reduction in the number of local government officers. Consequently, by 2022, the total number of local government officers had decreased to 2.8 million, reflecting a reduction of 480,000 personnel compared to 1994 [4]. Studies such as Numao (2016) have highlighted that this downsizing resulted in a shortage of human resources needed to operate LTCI. In short, the decentralization policy, described in the following section, was launched under challenging conditions, with municipalities facing significant resource constraints.

2.2. Roles of municipalities in Japanese LTCI

To address the challenges of an aging population, the Japanese government established LTCI in 2000 as a mandatory social insurance program with universal coverage. However, only half of its costs are financed through insurance premiums, with the remaining costs funded by general revenues: 25% from the national government and 12.5% each from prefectures and municipalities. This financial composition has remained unchanged despite the decentralization policy.

[4] Source: Reports of the Study Group for the Total Number Management of Civil Servants in Local Governments.

Under the LTCI framework, municipalities serve as insurers. LTCI insurers may either be individual municipalities, including Tokyo Special Districts, or unions of multiple municipalities (*koiki rengo* or *ichibu jimu kumiai)*[5]. The Japanese government regarded LTCI as an important measure to enhance local autonomy, referring to it as "a touchstone for decentralization" (Ministry of Health and Welfare, 2000). In other words, at the time of its introduction in 2000, decentralization was already a significant aspect of Japan's local governance, and LTCI aligned with this policy direction. Furthermore, Miyazaki (2018) reported that public service spillover influenced consolidation decisions during the Heisei mergers, potentially spurred by long-term care provision. However, as noted earlier, the achievement of Heisei mergers was limited, and several small municipalities remain in existence.

Insurers are responsible for planning and financing LTCI operations and certifying care-need levels. For planning, insurers predict future demand and invite additional long-term care service providers if necessary. Based on the prediction, they determine the premium, paid by all older adults (65+), to balance demand and supply.

The certification process of care-need levels is summarized in Tsutsui and Muramatsu (2005). Certification committees, appointed by insurers, calculate the minutes of long-term care required and assign one of seven care-need levels to recipients. These levels include Assistance Required (AR) 1 and 2 and care-required (CR) 1 through 5, with higher levels indicating greater care needs. If the required care minutes less than 25 minutes per day, no care-need level is assigned.

Care-need levels dictate services available, the monetary coverage limit, and the unit price of services. Notably Japanese LTCI provides only in-kind benefits, with no cash allowance. Kurimori *et al.* (2006) and Kurimori *et al.* (2010) demonstrated that these care-need levels effectively correspond to quality-of-life measures, justifying their use as indicators of older adults' well-being. The certification procedure remained consistent throughout the study period, unaffected by the introduction of MUO.

The certification of care-need levels occurs as follows. The first certification happens

[5]As of 2021, Japan had 1,578 insurers, of which only 40 were municipal unions.

upon request from eligible individuals. Updates of the assessed levels occur upon users' requests at any time, or through mandatory checkups, with the next mandatory checkup scheduled at the time of the certification. LTCI sets two standard schedules of the checkup, while the certification committees can set different schedules. Six months is a standard for updates following a new assessment, user-request updates, or mandatory updates involving changes in care-need categories between AR and CR. Twelve months is a standard for mandatory updates without changes between AR and CR categories.

Premium rates for LTCI reflect significant regional disparities. In 2018, the insurers with the highest and lowest premium rates were Tenkawa at JPY 8,686 (USD 72[6]). and Mishima at JPY 2,800 (23 USD), respectively. Thus, the highest premium was approximately thrice the lowest premium. A notable case is Otoineppu village in Hokkaido, where the premium was second-lowest at JPY 3,000 (USD 25) in 2018. This municipality had no institutional care facilities such as nursing homes because the local authority gave up providing such services. Consequently, residents requiring institutional care had to relocate to other municipalities. This lack of expensive institutional services allowed the municipality to maintain a low premium rate.

2.3. Detailed description for MUO

In this study, we evaluate MUO, introduced between 2015 and 2017 as an LTCI amendment targeting beneficiaries with the two lightest care-need levels, AR1 and AR2. These care-need levels accounted for approximately 1.8 million individuals, or 27% of all certified LTCI recipients, but represented only JPY 334 trillion (USD 2.8 trillion), or 4% of its costs as of March 2018[7].

In 2021, the Ministry of Health, Labour and Welfare (MHLW) proposed extending MUO to include CR 1 and 2 care levels. However, this plan was postponed because of the immature provision scheme of current MUO services and the disruption caused

[6]Throughout this research, we use the exchange rate in January 5th 2015, 1 USD = 120.41 JPY, taken from the Bank of Japan homepage (https://www.boj.or.jp/statistics/market/forex/fxdaily/ex2015.pdf, in Japanese).

[7]Source: Annual Report on Long-Term Care Insurance.

by the coronavirus disease 2019. Strong opposition by care providers and users, citing reduced quality and accessibility under MUO (Ueno and Higuchi, 2023), further delayed the extension. Active discussions about this expansion of MUO were ongoing as of 2025.

Under MUO[8], insurers can determine the content and pricing of three care services: home care[9], daycare, and "other daily living support". While home care and daycare services have been provided under conventional LTCI, other daily living support is a new addition under MUO. Other conventional LTCI services, such as home health care and all institutional care[10] were not covered under MUO and remained as in the conventional LTCI scheme. Home care and daycare constitute the largest share of at-home services. In 2014, these services accounted for 20.1% and 39.9% of remuneration points for AR1 and 2 recipients, respectively[11]

Before MUO, the central government uniformly defined the components and prices of care services, including home care and daycare. However, some municipalities independently provided additional support services, such as assistance with outings and food delivery, outside the LTCI framework. MUO integrated these services into LTCI under the category of other daily living support.

At the same time, MUO was introduced as a cost-reduction measure through a deregulation policy. MHLW aimed to reduce the growth in annual costs of AR1 and AR2 services from 6–7% to 3–4 %, aligning with the growth rate for the population aged 75 years or more. This target implied an expected approximately 3% reduction in AR service costs[12]. To achieve cost reduction, MUO allowed insurers to use a broader range

[8] For details, refer to MHLW guidelines, available at `https://www.mhlw.go.jp/file/06-Seisakujouhou-12300000-Roukenkyoku/0000192996.pdf` (in Japanese) and the report submitted by MHLW to the Central Social Insurance Medical Council on September 12, 2022, available at `https://www.mhlw.go.jp/content/12300000/000988262.pdf`, p.45 (in Japanese).

[9] In this study, the term "home care" represents a specific service under LTCI, while the term "at-home care" is a general term that includes long-term care services used by those who live in their own homes.

[10] See Tamiya *et al.* (2011) for an overview of LTCI services and Sugawara (2022) for at-home services.

[11] Source: Annual Report on Long-Term Care Insurance.

[12] This target was met until 2021, according to a report submitted by MHLW to the Central Social Insurance Medical Council on September 12, 2022, available at `https://www.mhlw.go.jp/content/`

of service providers, including volunteers and Non-Profit Organizations, with fewer staff qualification requirements. Previously, all providers had to meet national certification standards, but under MUO, insurers could establish their own criteria.

Although insurers have flexibility in designing MUO services, MHLW provided a typical service menu, in which home care was categorized into conventional and A—D subtypes, daycare into conventional and A—C, and other daily living support. These MUO services can be separated into three groups. The first is conventional services, which remained unchanged from the previous LTCI scheme, comprising conventional home care and conventional daycare. Conventional home care involves caregivers visiting the homes of users and includes direct care such as meals, toileting, and bathing, as well as indirect assistance such as cleaning, laundry, shopping, and cooking. Conventional daycare offers functional training, daily living support, and social activities in a facility during daytime.

The second group comprises deregulated services provided with relaxed staffing requirements, represented as home care A and B and daycare A and B services. Home care A and B services are focused on daily living assistance rather than direct care. While home care A is provided by professionals with lower qualification requirements, home care B is volunteer-based. Daycare A and B services emphasize group activities rather than functional training. Similar to home care, daycare A is provided by professionals with lower qualification requirements, while daycare B is volunteer-run.

The third group consists of new services introduced under MUO and includes home care C and D, daycare C, and other daily living support services. Home care C services involve health guidance from visiting public health nurses (*hokenshi*) or other medical or welfare professionals, while home care D services cover transportation assistance for hospital visits or daily activities. Daycare C is a short-term (3-6 months) functional training program. Other daily living support services include food delivery, monitoring of older adults, and life support, which combines home care and daycare services. Previously provided by municipalities, these services were integrated into LTCI under

`12300000/000988262.pdf` (in Japanese)

MUO. The above contents serve as examples and insurers have the flexibility to design any other service to meet local demand. Thus, the third group of the services form the primary component of MUO as a decentralization policy.

Prices for conventional services are capped at former LTCI levels, which were uniform across the country before MUO. Insurers are free to set prices for other services. For deregulated and new services, insurers set prices within a budget constraint based on past expenditures and the growth rate of the population aged 75 years and above.

2.4. Descriptive analysis for MUOs

Table 1 here

As discussed later, our dataset does not allow us to distinguish between MUO service types as described above. Instead, this subsection analyzes the detailed implementation of MUO using publicly available information. Table 1 presents the number of insurers that adopted MUO at different times. While the policy was introduced in April 2015, the central government allowed insurers to implement it at their discretion until April 2017. Adoption was not evenly distributed—more than 60% insurers implemented MUO in the final month, April 2017. Furthermore, April was a popular choice for implementation, likely because it marks the beginning of Japan's fiscal year. These patterns suggest that the timing of MUO adoption was not random and may be correlated with policy outcomes.

Next, we present several descriptive statistics at the aggregate level for 2017[13], after MUO adoption. The number of providers for conventional and non-conventional services was 31,927 and 11,159 for home care and 39,558 and 10,061 for daycare, respectively. Non-conventional services were available in 883 municipalities for home care and 1,006 for daycare out of Japan's 1,645 municipalities. Thus, while deregulated or new MUO services were available in over half of municipalities, only 25% of home care providers

[13]Source: Report on Preventive Long-Term Care and Daily Living Support 2017 in MHLW homepage, available at `https://www.mhlw.go.jp/file/06-Seisakujouhou-12300000-Roukenkyoku/0000211813.pdf` (in Japanese).

and 20% of daycare providers offered them. Among deregurated or new services for home care, shares of providers for A, B, C, and D services were 89.6%, 3.7%, 6.3%, and 0.4%, respectively. For daycare, shares of providers for A, B, and C service types were 67.6%, 9.0%, and 23.3%, respectively.

The numbers for deregulated and new services have been increasing since 2017[14], although conventional services remain dominant in terms of the number of users. In 2019, the shares of conventional and A service type users were 85.0% and 14.1% (shares for B, C, and D were less than 1%) for home care, while the shares of conventional, A, B, and C type users were 87.4%, 9.6%, 1.9%, and 1.2%, respectively, for daycare. For other daily support, only 22.5% of municipalities offered any such services in 2020, with monitoring services, food delivery, and other services provided in 7.5%, 19.6%, and 2.7% of municipalities, respectively.

These descriptive statistics yield three implications. First, the share of conventional services remains dominant in home care and daycare. This demonstrates that MUO has not drastically transformed LTCI. Second, apart from conventional services, deregulated services (home care A and B and daycare A and B) account for most non-conventional services, while new services have a limited presence. Third, other daily support services are underutilized, with more than three-quarters of insurers not providing them. These findings suggest that MUO's impact has been more pronounced in deregulation than in decentralization through new services.

Table 2 here

Next, Table 2 presents descriptive statistics on regional inequality before and after MUO. It shows proportions of care cost expenditures relative to the maximum allowable threshold for each care-need level among insurers in 2014 and 2019. Even before MUO, AR1 and AR2 had lower average rates and larger Gini coefficients compared to CR levels[15]. After MUO, these rates declined further, and Gini coefficients increased for AR1

[14]Source: a report submitted by MHLW to the Central Social Insurance Medical Council on September 12, 2022, available at `https://www.mhlw.go.jp/content/12300000/000988262.pdf`, (in Japanese)

[15]Fu *et al.* (2017) found that AR1 and AR2 services became less popular among users than CR services

and AR2, while CR levels remained largely unchanged. These findings imply that MUO has widened regional inequality in accessibility to AR services across municipalities.

3. Methods and data

3.1. Staggered DID method for policy evaluation

In this analysis, we evaluate MUO's impact on both input and output variables. For input, we analyze both extensive and intensive margins using monthly panel data. For output, we examine care-need transitions to evaluate the well-being of care users at the timing of LTCI certification updates. As the number of observed updates is limited for each individual, we utilize cross-section data for the output analysis.

When policy timing correlates with outcomes, traditional DID or event study estimators for policy evaluation can be biased (Goodman-Bacon, 2021; Baker *et al.*, 2022). Specifically, if the ATT for post-treatment periods is estimated as a single parameter, it becomes a weighted average of ATTs across various adoption timings. However, in simple DID estimation, both the weights and the summand may be inconsistent. To address this problem, we adopt a staggered DID approach to avoid bias.

We firstly employ two diagnostic methods for the potential bias, proposed by Jakiela (2021). The first method involves calculating the weights and checking their signs. If negative weights appear, it indicates potential bias. The second method involves checking correlations between residualized outcomes and treatment. If these residuals have linear relationships, no heterogeneities exist in treatment effects; hence, ATTs for various timings can be estimated without bias. As shown in Subsection 4.1, biases are present both on weights and ATTs for various timings in our dataset. As these methods require panel data, we apply them only to input analysis.

For staggered DID, we primarily follow the approach of Callaway and Sant'Anna (2021), which accommodates both panel and cross-sectional data. This method estimates ATTs using inverse probability weight estimators and defines corresponding weights

levels after the 2006 amendment of LTCI, which restricted the use of indirect care in home care.

appropriately. We can include covariates as conditioning variables for the parallel trend hypothesis. In panel data, the covariates must be time-invariant. In ATT estimations for post-treatment periods using Callaway and Sant'Anna (2021)'s method, we adopt not-yet-treated observations as the control group because all insurers were eventually treated in our dataset. To check the robustness of our analysis, we also apply the estimation methods of Sun and Abraham (2021) and De Chaisemartin and d'Haultfoeuille (2024), which is a dynamic extension of De Chaisemartin and d'Haultfoeuille (2020)[16].

To obtain unbiased estimators from the staggered DID approach, we assume that MUO did not alter care recipients' living arrangements. No anecdotal evidence suggests increased relocation due to MUO, likely because its long-term care costs were marginal. In 2014, services for AR recipients (MUO users) accounted for only 5.8% of total LTCI remuneration points[17]. Therefore, not reacting to MUO costs is natural.

Additionally, MUO services are primarily provided within an insurer's jurisdiction. Unlike standard at-home LTCI services, where users can receive care from providers outside their insurers, MUO providers must obtain approval from each insurer they operate under. Although no statistics exist on multi-jurisdictional providers, such cases seems to be rare. Therefore, we do not consider cross-border care purchases in our analysis.

3.2. Data

3.2.1. Definition of our sample

Our empirical analysis is based on a nationally-representative dataset of individuals derived from administrative records of LTCI claims and care-need certification. These records are sourced from the Survey of Long-term Care Benefit Expenditures conducted by MHLW (MHLW, 2006-2019). The survey includes claims examined by MHLW up to April 2018, although some claims extend beyond this due to processing delays. For this

[16] We do not adopt the method of Borusyak *et al.* (2024) because it requires observations without any treatment.

[17] Source: Annual Report on Long-Term Care Insurance.

study, we utilize claims data from May 2014 to November 2019.

Our dataset captures claims from over 90% Japanese municipalities, covering more than 80% of all LTCI users. However, some municipalities do not permit secondary data use and are therefore excluded. Although the LTCI also covers individuals aged 40–64 years with aging-related diseases, our analysis focuses on older adults aged 65 years and above.

We specifically examine individuals certified as AR1 or AR2, as they are eligible for MUO. To obtain more detailed insights, we employ additional analysis using subsamples of individuals living in small and large municipalities. In this analysis, we exclude individuals residing in municipalities where LTCI is administered by municipal unions.

3.2.2. Variables for input analysis

For the extensive margin, we use a dummy variable that takes a value of one when an individual utilizes care services and zero otherwise. To evaluate the policy effects from multiple perspectives, we consider four dummy variables representing distinct care services: any LTCI service, any MUO service, home care, and daycare. Daycare includes both community-based daycare and ordinary daycare. The MUO services include daycare, home care, and other daily living support, which appeared in our dataset only after MUO implementation because it was not previously covered by LTCI. Furthermore, distinguishing between MUO service types in the claims data is challenging for home care and daycare[18].

For the covariates in the extensive margin analysis, we include three time-invariant variables. The first is a dummy variable for males. The second is an AR2 dummy variable, which takes a value of one if the individual is certified as AR2 and zero if their certified level is AR1. If the individual updates their certification and receives a different level, they are excluded the individual after the change from the analysis. The

[18]The rules on claims about MUO services are outlined in the MLHW announcement of 24th February 2015, available at https://www.mhlw.go.jp/file/06-Seisakujouhou-12300000-Roukenkyoku/0000188226.pdf (in Japanese)

third variable is the age in the first observed month. The inclusion of this variable has a potential problem as older people tend to have worse health and use more services. To overcome the problem, we conduct a robustness check by treating each age change as a separate cross-sectional unit. However, because this approach limits observation periods to a maximum of 12 months and includes a same individual as different cross-sectional units, we do not consider it our primary analysis.

For the intensive margin, we utilize expenditures and days of use of a service. The expenditure is measured in remuneration points, typically converted to 10 JPY per point, although regional variations exist. We concentrate on months when an individual actually uses a care service (i.e., the months where the above utilization dummy takes a value of one). Corresponding to the four distinct utilization dummy variables, we analyze expenditures for the four categories. For days of use, we only analyze MUO services, home care, and daycare, because measuring usage days for several LTCI services such as equipment rental is not meaningful.

For covariates of intensive margin analysis, we include three variables used for the extensive margin analysis, plus the LTCI coinsurance rate, which is reassessed annually in August based on income. Most users pay 10%, while social welfare recipients pay 0% and high-income individuals pay 20%. This variable cannot be used in the extensive margin analysis because it is not observed when the usage dummy takes the values of zero. To keep this variable time-invariant, we exclude observations where an individual's rate changes, removing 4.76% of observations.

Finally, we combine extensive and intensive margin analyses to assess total care costs per individual. In this analysis, the costs are set to zero when the usage dummy is zero. We evaluate total LTCI service costs in JPY, multiplying the remuration points and the exchange rate.

3.2.3. Variables for output analysis

For output analysis, our outcome variable is the transition in care-need certifications. Similar to the intensive margin analysis, we separately analyze four targets, users of any

LTCI services, any MUO services, daycare, and home care. We exclude individuals who did not use corresponding services during the certification periods, as our focus is on care-need transitions among service users.

In this analysis, the time unit is redefined from a calendar month to a certification period. Specifically, a certification period is the interval that begins in the month which a certification is received and ends one month prior to the subsequent certification. An individual is defined to be treated if the certification periods include at least one month under MUO. To measure the transition, we primarily analyze a dummy variable that equals zero if their care-need level becomes worse and unity if the status is unchanged or improved at the next certification. Additionally, we also adopt another outcome variable that equals zero if their care-need level becomes worse, unity if the status remains unchanged, and two if the status is improved. We call this variable a transition score. For simplicity, we report transition scores only for MUO service users.

Transitions to CR levels are classified as worsening, regardless of the prior care-need level. Other forms of attrition, such as death, transitions to a state without a care-need level (which may reflect either improvement or deterioration, including recovery or end-of-life care at home without LTCI services), and relocation to a different municipality, are treated as missing data.

The number of certification updates for each individual is small. Specifically, the means are 4 for non-treated and 5.2 for treated, as shown in Table 3. To account for this, we construct a cross-sectional dataset where each certification update is treated as a separate observation. To capture the complex dynamics involved, we also conduct a robustness check using panel data.

For covariates, we include all variables used for intensive margin analysis. For the coinsurance rate, we introduce the average values for months with positive LTCI service use during the certification period. Furthermore, as the output analysis uses cross-sectional data, we can include time-variant covatiates. Then, we include the length of the certification period before the transition and the number of LTCI certifications up to the transition to control the time-varying status of individuals.

3.2.4. Descriptive statistics

Table 3 here

Table 3 presents the descriptive statistics. As the analysis for (1) extensive margins, (2) intensive margins, and (4) care-need transitions utilize different datasets, we provide separate numbers of observations for each. For intensive margins and care-need transitions, we analyze distinct populations—users of any service, MUO services, home care, and daycare. For simplicity, we report descriptive statistics of outcomes and covariates only for the sample of MUO service users in (2) and (4). For the other services, we report the descriptive statistics of outcome variables in Appendix Table A.1. As the cost analysis (3) uses the same dataset as the extensive margin analysis (1), we omit descriptive statistics for covariates in this section.

The sample size is larger for the extensive margin analysis than for the intensive margin analysis because the latter excludes individuals who did not use care services. The sample size is further reduced for the care-need analysis, which uses certification updates as the time unit. In Part (4), the mean values of the care-need transition dummy and the score are comparable. This similarity indicates that improvements in the care-need level are infrequent when observed on a monthly basis.

4. Results

4.1. Diagnosing bias in simple DID

Figure 1 here

To assess potential bias in simple DID estimation, we apply Jakiela (2021)'s diagnostic to input variables, focusing on outcome variables for MUO services. Figure 1 illustrates the results of the diagnosis. As this method does not apply to cross-sectional data, we do not use it for output variables.

Panels in the left column of Figure 1 show weight estimation diagnostics. In all three outcome variables, negative weights emerge in later months, indicating a risk of biased weights in simple DID estimators. Panels in the right column of Figure 1 illustrate residualized outcomes and the treatment status, showing no clear linear relationships between the two residuals. This suggests potential bias in ATT estimations across different treatment timings. Thus, all our outcome variables for input have a risk of potential bias. Given these results, we adopt the staggered DID method for our dataset.

4.2. Visualizing event study results

Figure 2 here

Before discussing ATT estimates in detail, we first examine the validity of the staggered DID approach using graphical analysis. Figure 2 illustrates event study analysis for outcome variables related to MUO services using Callaway and Sant'Anna (2021)'s method. Although our dataset includes more months in observations, we show only 12 months before and after the treatment in Figure 2, because of limited observations beyond that period.

Figure 2 demonstrates that in all cases, pre-treatment coefficients remain around zero, supporting the parallel trend assumption[19]. Furthermore, post-treatment ATTs decline monotonically over time for all variables, indicating that the policy's effects are not temporary but persistent. Detailed estimates are discussed in the next subsection.

Figures 3 and 4 here

To test the robustness of our findings, we apply alternative staggered DID estimators from Sun and Abraham (2021) and De Chaisemartin and d'Haultfoeuille (2024). Figure 3 illustrates event study results for input variables using these methods. As some methods are computationally burdensome, we use a 10% random sample for this analysis[20]. We also illustrate the results using Callaway and Sant'Anna (2021)'s method because this

[19] However, statistical tests for parallel trends do not confirm the hypothesis. This might be because our monthly dataset includes numerous treatment timings and demonstrating that ATTs for all pre-treatment timings are zero is difficult.

[20] We also employ the same analysis using 30% random sample and obtain similar results.

randomized sample differs that from our main analysis in Figure 2. In Sun and Abraham (2021), the ATT for the period just before the treatment is set to zero. Figure 4 illustrates the event study results for the care-need transition dummy using De Chaisemartin and d'Haultfoeuille (2024). We do not use Sun and Abraham (2021)'s method for care-need transitions, as it is designed for panel data.

Panels in the upper row in Figure 3 display results for the usage dummy, where Sun and Abraham (2021)'s estimator does not satisfy the parallel trend assumption. The bottom panels display results for days of use. Our main results using the whole sample in Figure 2 indicate negative treatment effects in later months. However, in Figure 3, even Callaway and Sant'Anna (2021)'s estimates are insignificant, likely due to the small sample size. Furthermore, for days of use, De Chaisemartin and d'Haultfoeuille (2024)'s method also yields insignificant ATTs for most post-treatment months, whereas Sun and Abraham (2021)'s method obtains positive treatment effects for several months. These findings indicate that our estimation is not robust for the usage dummy and days of use; therefore, we do not interpret results for these variables intensively in the subsequent subsections.

By contrast, estimated ATTs for remuneration points and care-need transitions consistently show the similar treatment effect direction across methods, supporting the robustness of our findings.

4.3. Estimation results for ATTs

Table 4 here

Table 4 presents the estimated ATTs for the entire post-treatment months using Callaway and Sant'Anna (2021)'s method, where standard errors are clustered at the insurer level. We do not estimate clustered standard errors at the indivicual level, because in this method, clustering standard errors for cross-sectional units is not feasible.

Part (1) of Table 4 shows results for extensive margins. All variables exhibit significantly negative treatment effects at the 10% level. However, the coefficient estimates are small with 0.4% to 0.7% declines. Given the instability of usage dummy estimates across methods other than Callaway and Sant'Anna (2021) in Figure 3, we conclude that MUO had only marginal impacts on extensive margins.

Part (2) reports results for intensive margins. All post-treatment ATTs for remuneration points are significantly negative at the 1% level. Compared to descriptive statistics in Table 3, the reductions of remuneration points amount to 1.5%, 2.4%, 2.0%, and 2.2% for all services, MUO services, home care, and daycare, respectively. For days of use, estimated ATTs are not significant at the 10% level; therefore, we do not provide intensive interpretation for this variable.

Part (3) of Table 4 presents results for costs, with an estimated ATT of JPY -618.6 (USD 5.1), corresponding to a 2.8% reduction. This amount aligns with the government's intended goal of lowering the long-term care cost growth rate from 6-7% to 3-4%. As shown in Subsection 2.3, the realized cost reduction appears similar to policymakers' expectations for MUO as a deregulation incentive. As mentioned above, we conclude that MUO had considerable negative effects on the remuneration points, while its effects on the usage dummy and days of use remain indecisive. The significantly negative effects on costs are caused by the negative effects on remuneration points, that is, the reduction of expenditure among users.

Part (4) displays estimation results for care-need transitions, where all treatment effects are significantly negative at the 1% level. The transition dummy variables indicate negative effects of 3–4%. Compared to descriptive statistics in Table 3, which shows less than 2% of individuals transitioning to a worse care-need status per certification update, MUO increases the likelihood of deterioration by 131%, 133%, 146%, and 125% for users of any service, MUO service, home care, and daycare, respectively. The result for the transition score is similar to that of the care-need transition dummy. As the two variables have similar sample means in Table 3, this is a natural finding.

4.4. Additional analysis for small and large municipalities

We further analyze the relationship between regional inequality and MUO using subsamples of small and large municipalities, which correspond to populations smaller than

10,000 and larger than 500,000 based on the 2015 Population Estimate, respectively. Among the 1,742 municipalities, 486 are small and 45 are large, while our dataset includes 21,108 and 73,350 individuals, respectively, for the usage dummy analysis.

Table 5 here

Table 5 presents results for the usage dummy and remuneration points for MUO service for small and large municipalities. Given the small sample size in many municipalities, we do not use clustered standard errors. The estimated ATTs for usage dummies are not significant for both small and large municipalities. However, for remuneration points, the estimates are significantly negative, with magnitudes 1.5 times larger in small municipalities. This suggests that decentralization has a greater impact on residents in smaller municipalities.

4.5. Discussion

Our analysis indicates that the 2.8% reduction in per-user costs. While cost reductions can theoretically lower co-payments and increase care access, our findings from the input analysis do not support this hypothesis. Although we obtained indecisive results in some robustness tests, we can reasonably conclude that the amount of service use was not much changed, indicated by the unchanged or slightly reduced likelihood of using care services and by unchanged days of use before and after the policy. However, expenditures among users significantly declined, suggesting that the unit price for care services decreased, while the usage amounts did not change significantly after MUO. This is consistent with aggregate-level descriptive analysis in Subsection 2.4, which shows that apart from conventional services, deregulated services accounted for most of MUO usage and the new MUO services were rarely implemented. In this point, the amount of expenditure for the other daily living support is distinguishable in our dataset, but the utilization rate after MUO's introduction is only 0.0003, indicating its limited popularity of the new MUO service.

These results for input analysis differs from the results of some previous studies on deregulation in health economics, including Wing and Marier (2014), where a deregulation policy expanded business opportunities in the dental care context. Furtheremore, a recent report from the Japan Federation of Long-Term Care Business Providers (*Zenkoku Kaigo Jigyosha Renmei*)[21] highlights regional differences in MUO's rewards and requirements, which have led some providers to exit services for AR1 and AR2. As our study lacks supply-side data, we do not analyze such a provider behavior directly. However, if supply declines, access to services for AR1 and AR2 may become more difficult, suggesting that MUO acted as a barrier to entry rather than an expansionary opportunity for providers.

Our output analysis indicates that LTCI users experienced worsening care-need transitions due to MUO, with negative transitions increasing by more than 120%. Given that our results from inputs indicated that the usage amount had remained largely unchanged, a reasonable interpretation is that deregulation led to a decline in service quality. This conclusion aligns with the research on the positive effects of minimum staffing requirements in US nursing homes (Zhang and Grabowski, 2004).

The above interpretations indicate that under the local population shrinkage, the benefits of flexible operations from decentralization were insufficient to offset the decline in care quality. From a regional policy perspective, as shown in Table 2, MUO widened regional inequality. Table 5 further indicates that expenditure reductions were more pronounced in smaller municipalities. A likely explanation is that smaller municipalities have limited human resources to achieve scale economies as population is highly correlated with the number of officers [22] Based on these findings, future MUO extension, which is planned by the government as mentioned in Subsection 2.3, requires careful

[21] Source: Japan Federation of Long-Term Care Business Provider's report to the Council for Sufficient Preventive Long-Term Care and MUO, May 31, 2023, available at `https://www.mhlw.go.jp/content/12300000/001102052.pdf` (in Japanese).

[22] The correlation coefficient between population and the number of ordinary account municipality officers is 0.98, excluding designated cities with more than 500,000 population, as shown in the 2018 Report of the Study Group for Total Number Management of Civil Servants in Local Governments. Even for designated cities, a correlation coefficient was shown to be 0.8116 in the same report for 2010.

consideration.

Beyond, the shortage of local resources, legislative factors may have contributed to the failure of decentralization. OECD (2019) emphasized that successful decentralization depends on cooperation among local authorities, which was lacking under MUO. As noted in Shakai hoken kenkyu jo (2019), prefectures, the higher level local authorities than municipalities, supervise municipal service provision, fostering collaboration in public health policies, as shown in Bessho and Ibuka (2019). However, MUO services were managed primarily at the municipal level, with little coordination between municipalities or with prefectures.

Consequently, our study shows that the policy effect can be limited under local population decline. When the LTCI system was introduced, Japan's population was still increasing, making municipal empowerment a viable option. However, continuous population aging and depopulation have altered the situation. The resultant lack of resources has burdened local authorities and no successful mechanism exists for local cooperation to compensate for the resource constraint. Consequently, effective decentralization remains a challenging task under local population shrinkage.

In addition to the above main findings, two additional insights emerge from our empirical results. First, the worsening care-need transition was more pronounced for home care users than for daycare users. One potential explanation can be found in Sugawara *et al.* (2024), which highlights daycare's multifunctional role in Japan's LTCI, serving as both caregiver respite and a substitute for other services such as rehabilitation. Thus, relatively more demanding functions such as rehabilitation may have remained in conventional services, while those with milder needs moved to daycare A and B. By contrast, home care services may have lacked a similar dispersion of service levels, leading to a direct reduction in care quality.

Second, we find a clear dynamic trend in our results. As shown in Subsection 4.2, the magnitude of policy effects increased over time across all variables. As mentioned in Subsection 2.3, the conventional services for home care and daycare are expected to be replaced by deregulated and new MUO services. Thus, we can reasonably interpret that these negative trends are caused by the gradual replacement of the derefulated and new MUO services. Note that as shown in Subsection 2.4, even after the MUO, conventional services still account for a significant share of long-term care provision. If further replacements occur beyond our study period, these negative effects could become even more pronounced.

4.6. Robustness check

Table A.2 here

To check the robustness of our results, we conduct two additional analyses. First, Table A.2 presents estimated ATTs for MUO services in input analysis, treating individuals at different ages as distinct cross-sectional units, as described in Subsection 3.2.2. This approach addresses the challenge posed by time-invariant covariates in panel data. As our output analysis already employs cross-sectional data, this method is not applied there. The estimated results in Table A.2 are broadly consistent with our main analysis, reinforcing the robustness of our findings.

Second, we analyze care-need transitions using panel data to control individual fixed effects, as discussed in Subsection 3.2.3. Given the limited number of observed periods per individual, we focus on those with four or more certification updates. In this panel data analysis, only time-invariant covariates, the individual's age at first observation and the average coinsurance rate across all observed months, are included, consistent with our extensive margin analysis. For the care-need transition dummy among MUO service users, the estimated ATT for the post-treatment periods and its standard deviation are -0.021 and 0.004, respectively, significant at the 1% level. Thus, we obtain a significantly negative policy effect for care-need transition, which is consistent with our main results, further supporting their robustness.

5. Conclusions

In this study, we evaluated Japan's decentralization policy for public long-term care using a staggered DID method. Our empirical analysis showed that while the policy reduced individual expenditures, it also increased their care-need levels, suggesting that the advantage of operational flexibility was offset by declining service quality. Our findings highlight the difficulties of implementing decentralization policies in aging and shrinking local communities.

Despite these insights, our analysis has certain limitations. First, we cannot assess the long-run effects of MUO using data up to recent periods. For claims examined after April 2018, the Japanese government has altered data-sharing policies, preventing the integration of claims data with municipality-level information such as the timing of MUO adoption. Consequently, our study is constrained to earlier periods.

Second, we do not account for details of government expenditures in establishing MUO, limiting out cost analysis to consumer-level expenses. While remuneration points provide a measure of user costs, we lack a comprehensive metric for costs borne by insurers and the central government in establishing MUO. Future research should incorporate a broader definition of costs to provide a more holistic evaluation of the policy's financial implications and cost-benefit analysis.

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Figures and Tables

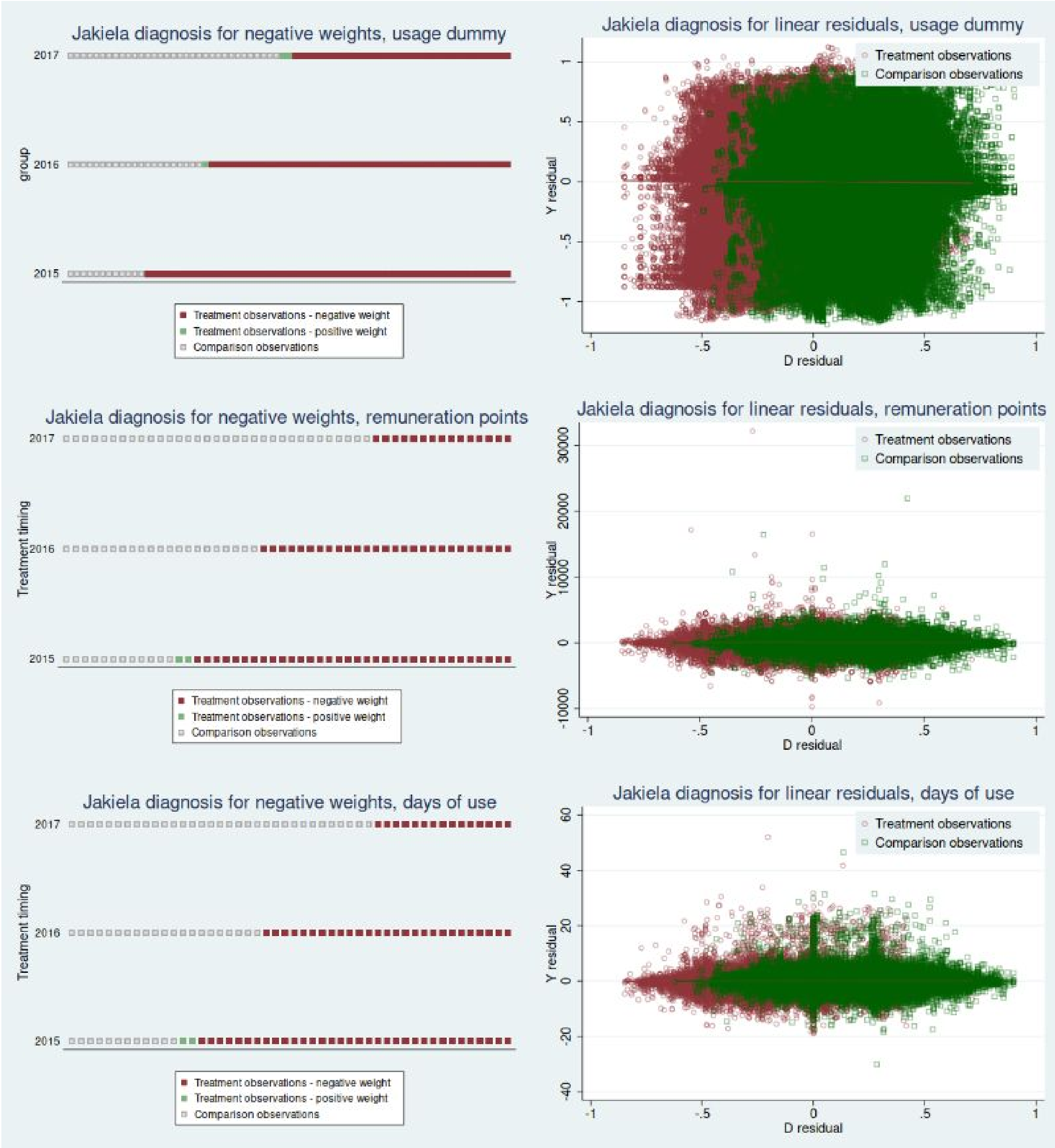

Figure 1: Diagnosis using Jakiela (2021)'s method. We present results only of outcome variables related to MUO services. Panels in the left column display diagnostics for weights while those in the right column show diagnostics for residuals. Panels in the upper row correspond to the usage dummy, the middle row to remuneration points, and the lower row to days of use.

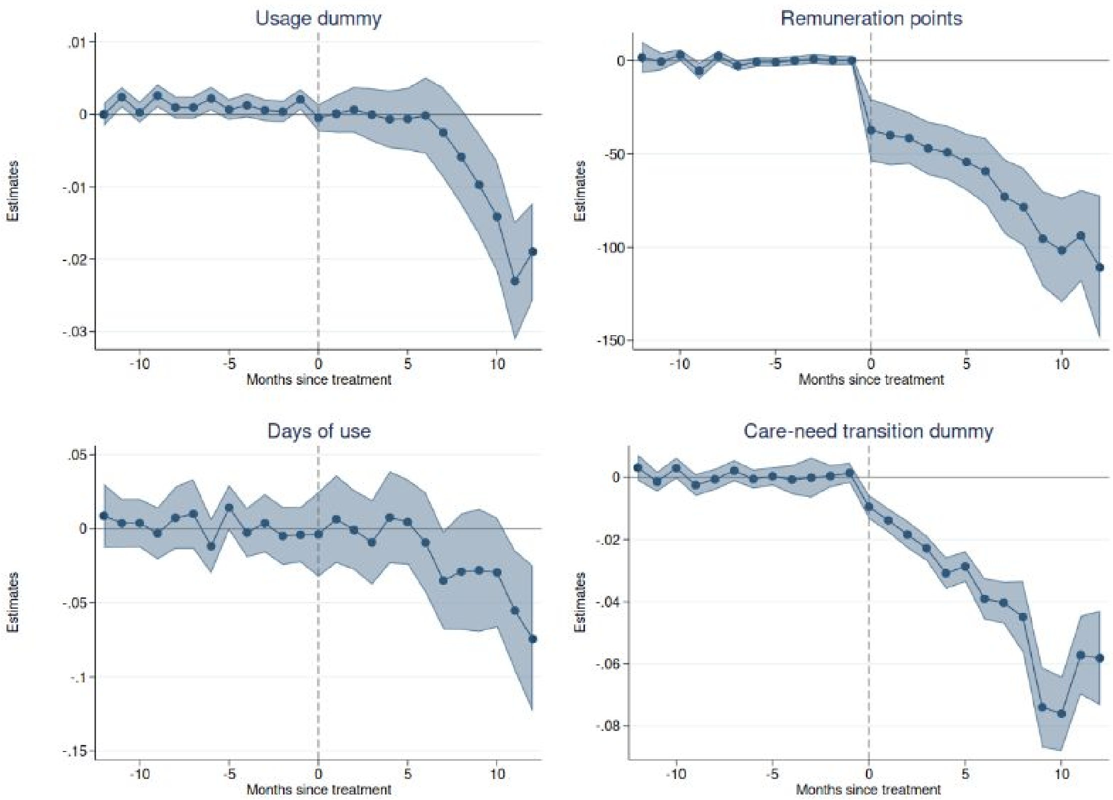

Figure 2: Event study analysis for Callaway and Sant'Anna (2021)'s method. We present results only of outcome variables related to MUO services.

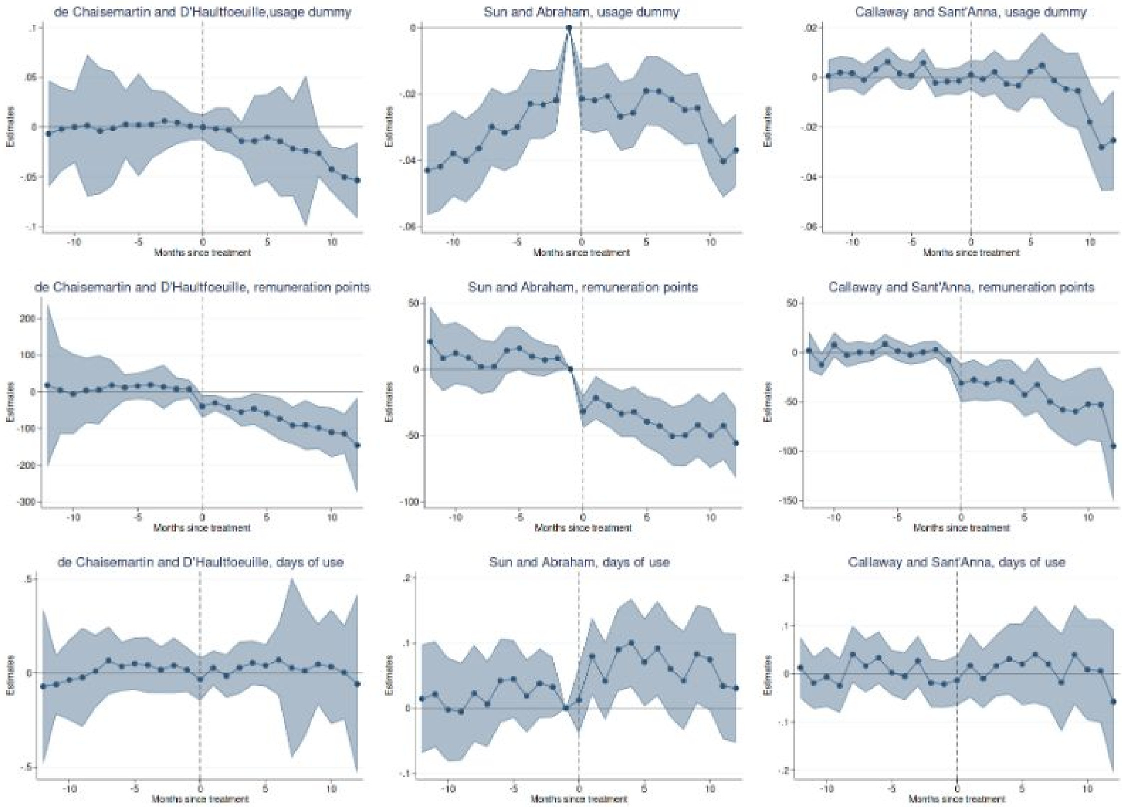

Figure 3: Event study analysis for extensive and intensive margins using alternative staggered DID methods. We display results only for outcome variables related to MUO services. Panels in the upper row correspond to the usage dummy, the middle row to remuneration points, and the lower row to days of use. Estimation is based on a 10% random sample.

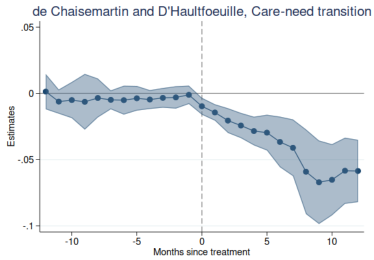

Figure 4: Event study analysis for care-need transition among MUO service users using alternative staggered DID methods.

Table 1: Number of insurers by timing of MUO adoption

Year	Month	N	%
2015	4	78	4.94
	6	1	0.06
	7	1	0.06
	10	14	0.89
	12	1	0.06
2016	1	27	1.71
	2	23	1.46
	3	142	9
	4	226	14.32
	6	1	0.06
	7	3	0.19
	10	59	3.74
	11	2	0.13
	12	3	0.19
2017	1	19	1.2
	2	11	0.7
	3	967	61.28
Total		1,578	100

Note: Source: Homepage of MHLW, `https://www.mhlw.go.jp/file/06-Seisakujouhou-12300000-Roukenkyoku/0000193022.xlsx`.

Table 2: Proportions of care cost expenditures relative to the maximum allowable threshold among insurers

	2014			2019		
	Mean	S.D.	Gini	Mean	S.D.	Gini
AR1	0.364	0.122	0.155	0.174	0.089	0.258
AR2	0.373	0.088	0.120	0.169	0.071	0.222
CR1	0.566	0.104	0.100	0.610	0.121	0.099
CR2	0.739	0.118	0.082	0.769	0.121	0.079
CR3	0.802	0.104	0.061	0.865	0.092	0.054
CR4	0.824	0.105	0.060	0.877	0.094	0.055
CR5	0.781	0.109	0.072	0.818	0.102	0.065

Note: The numbers represent descriptive statistics for insurers. Mean and S.D. indicate the average proportions of care cost expenditures relative to the maximum allowable threshold for each care-need level and its standard deviation, respectively. GINI refers to the Gini coefficient for the proportions. We consider only out-of-pocket expenses and assume that all users have a 10% coinsurance rate. Therefore, we adjust the out-of-pocket expenses by multiplying them by 9/10. Source: Annual Report on Long-Term Care Insurance by MHLW.

Table 3: Descriptive statistics

		Control		Treated	
		Mean	Std.	Mean	Std.
(1) Analysis for extensive margins					
Usage dummy	Any service	0.672	0.470	0.566	0.496
	MUO services	0.715	0.451	0.594	0.491
	Home care	0.331	0.471	0.258	0.437
	Daycare	0.431	0.495	0.387	0.487
Covariates	Male	0.259	0.438	0.257	0.437
	Age	81.8	6.7	83.2	6.8
	AR2 dummy	0.426	0.495	0.490	0.500
Observations		14,476,336		6,699,301	
(2) Analysis for intensive margins, MUO service users					
Remuneration Points		2,719	1,379	2,749	1,352
Days of use		6.32	3.55	6.58	3.70
Covariates	Male	0.232	0.422	0.232	0.422
	Age	81.7	6.7	82.7	6.8
	AR2 dummy	0.438	0.496	0.495	0.500
	Coinsurance rate	0.103	0.018	0.103	0.020
Observations		9,310,998		3,546,824	
(3) Analysis for costs					
Costs	All services	22,183	20,901	19,464	21,925
Observations		14,476,336		6,699,301	
(4) Analysis for care-need transitions, MUO service users					
Transitions	Dummy	0.980	0.139	0.970	0.170
	Score	0.987	0.162	0.983	0.206
Covariates	Male	0.234	0.423	0.240	0.427
	Age	82.0	6.6	83.3	6.7
	AR2 dummy	0.490	0.500	0.564	0.496
	Average coinsurance rate	0.106	0.024	0.108	0.028
	Months during certification	12.1	3.1	14.3	5.6
	Number of certifications	4.33	3.10	5.12	3.26
Observations		1,174,888		471,594	

Table 4: Estimated post-treatment ATTs for our main analysis

Outcome		Coef.	S.E.
(1) Extensive margins			
Usage dummy	Any service	-0.004	0.002
	MUO services	-0.007	0.002
	Home care	-0.006	0.001
	Daycare	-0.004	0.002
(2) Intensive margins			
Remuneration points	Any service	-49.50	9.32
	MUO services	-66.25	9.20
	Home care	-37.98	5.97
	Daycare	-59.48	9.58
Days of use	MUO services	-0.015	0.014
	Home care	-0.017	0.011
	Daycare	0.002	0.018
(3) Costs			
Costs	All services	-618.1	109.5
(3) Care-need transitions			
Dummy	Any service	-0.040	0.003
	MUO services	-0.040	0.003
	Home care	-0.046	0.004
	Daycare	-0.037	0.003
Score	MUO services	-0.027	0.004

Note: Only estimates for ATTs are reported. S.E. represents cluster standard errors for insurers.

Table 5: Estimated post-treatment ATTs for small and large municipalities

Outcome		Coef.	S.E.
Small municipalities	Usage dummy	0.005	0.007
	Remuneration points	-64.40	23.59
Large municipalities	Usage dummy	0.003	0.003
	Remuneration points	-43.11	8.14

Note: We focus on outcome variables for MUO services. Only estimates for ATTs are reported. S.E. represents standard errors. Small and large municipalities have populations below 10,000 and more than 500,000, respectively.

A. Appendix

A.1. Appendix tables

Table A.1: Descriptive statistics for abbreviated outcome variables

		Control		Treated	
		Mean	Std.	Mean	Std.
Remuneration Points	Any service	3,020	1,786	3,198	1,881
	Home care	1,878	851	1,926	911
	Daycare	2,798	1,013	2,730	964
#days of use	Home care	5.87	2.95	6.09	3.07
	Daycare	5.35	2.54	5.56	2.61
Transition dummies	Any service users	0.980	0.140	0.969	0.172
	Home care users	0.980	0.140	0.968	0.175
	Daycare users	0.980	0.139	0.970	0.170

Table A.2: Estimated post-treatment ATTs using panel data within age

Outcome	Coef.	S.E.
Usage dummy	-0.011	0.002
Remuneration points	-70.43	10.98
Days of use	-0.029	0.015
Costs	-711.02	119.36

Note: We focus on outcome variables for MUO services. Only estimates for ATTs are reported. S.E. represents cluster standard errors for insurers.