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ARTICLE

What composes desirable formal at-home elder care? An analysis for multiple service combinations

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Abstract

I estimate the relationship between combinations of multiple services for formal at-home elder care and health status. As a reasonable substitute for expensive institutional care, at-home formal elderly care is gaining popularity in developed countries. Because at-home care is composed of many small and complementary services, the relationship between multiple service combinations and health status requires analysis. However, the high dimensionality of these combinations makes estimation difficult. This study employs a regression analysis using care service combinations as cross-dummy explanatory variables. To reduce the combination dimensions, I select the combinations that are purchased jointly by a sufficient number of the elderly using basket analysis. I apply this method to claims data for Japanese long-term care, for which the social insurance program has resulted in the emergence of a market that offers many care services for the elderly. The empirical results show that only 200 combinations of 14 at-home care services are used by more than 0.03% of the insured in Japan. Of these combinations, rehabilitation services have a considerable positive correlation with the health status of the elderly. However, their use is limited owing to regional disparities in the location of such services.

Keywords At-home elder care · Multiple care services · High-dimensional data · Basket analysis · Long-term care insurance in Japan

JEL Classification J14 · I13 · I18

1 Introduction

Most developed countries are facing the dual problem of an aging population and increasing long-term care costs. Many governments subsidize the formal institutional care sector, which includes nursing homes. However, because institutional

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care is costly, many countries are seeking alternative care options. A conventional substitute for institutional care is informal at-home care[1] provided by family members (Chiswick 1976; van Houtven and Norton 2004; Charles and Sevak 2005; Bolin et al. 2008; Hanaoka and Norton 2008; Bonsang 2009; Balia and Brau 2014). However, this option has negative effects on family caregivers in terms of factors such as labor supply (Wolf and Soldo 1994; Van Houtven et al. 2013; Sugawara and Nakamura 2014; Fu et al. 2017), health status (Coe and Van Houtven 2009), and subjective well-being (Van den Berg and Ferrer-i Carbonell 2007; Niimi 2016).

Formal at-home care is now considered a reasonable substitute for institutional care. Even in cases where no market for formal at-home care exists, several researchers have considered the advantages of such a system (Carmichael and Charles 2003; Heitmueller and Inglis 2007; Heitmueller 2007; Carmichael and Charles 1998). Several countries have begun providing formal at-home care. As an empirical example, De Meijer et al. (2015) analyzed the Netherlands, where a social insurance program covers formal at-home care. The authors found that a shift in formal at-home care is the main reason for a decline in institutional care.

A distinct characteristic of at-home care is that the sector includes many small and complementary services. This is unlike medical care services provided by a hospital or institutional long-term care, both of which provide a single integrated care service. Instead, at-home care provides an appropriate combination of services based on the characteristics of the user, such as their health, economic status, and family structure. Thus, an analysis of multiple service combinations has rich implications in the context of home care.

The conventional approach to an analysis of the relationship between the use of combined services and health status is regression analysis with cross-dummies that correspond to the combinations as explanatory variables. However, the high dimensionality of the combinations creates difficulty in identifying the regression coefficients. When a combination of services is seldom used, the lack of degrees of freedom means that the coefficient for the corresponding cross-dummy variable is not strongly identified. Because there are many combinations, it is burdensome to check the identifiability of wach combination.

To solve this identification problem, I present a simple econometric method to handle the high-dimensionality problem of combinations. My method incorporates an itemset mining approach for dimension reduction. This step selects itemsets that are often used jointly via basket analysis. I construct cross-dummies that correspond to the obtained baskets and then apply regression analysis. This approach, which I call a *basket regression*, allows the analysis of all combinations used by a sufficient number of people.

I apply this method to large claims data for Japan. In 2000, with the world's most rapidly aging population, the country established Long-Term Care Insurance

[1] I use the term "at-home care" to refer to general care services for recipients who remain in their own homes. Conventionally, the term "home care" is often used for this purpose in health economics. In the Japanese context, as described in Sect. 2.2, home care refers to a specific service whereby a caregiver visits the home of an elderly person to provide care.

(LTCI), a mandatory social insurance program specific to long-term care. Of the countries that implement social long-term care insurance, Japan provides broader coverage for lighter disabilities, as summarized in Campbell et al. (2009). To supply care to the elderly with moderate disabilities, the Japanese LTCI provides generous coverage for at-home care. As a result, the country has formal markets for many at-home care services where the elderly choose the service combination. The combination is called a *care plan* by the Japanese LTCI system, and the appropriate construction of care plans represent a social issue.

My empirical study analyzes 14 services within long-term at-home care services. As an outcome variable, I use the transitions of care-need levels after using care services to reflect users' health status. The empirical results show that of the $2^{14} = 16,384$ possible combinations of 14 services, only 200 care plans are adopted by more than 0.03% of LTCI users. The results of the basket regression show that among several care plans that include a medical services, especially rehabilitation services, have a strong positive correlation with the health status of the elderly. However, the use of rehabilitation services may be limited owing to regional disparities in accessibility.

The proposed method contributes to an emerging body of literature that attempts to unify econometrics and machine learning. Machine learning provides various approaches to the handling of high-dimensional data. As more high-dimensional data become available in economics, adaptations of machine-learning methods are gaining popularity in econometrics, as surveyed by Mullainathan and Spiess (2017).

The novel aspect of this research is that I concentrate on high-dimensional data composed of multiple variable combinations. For analysis of high-dimensional combination data, there is a literature body on machine learning from the perspective of multiple testing. Terada et al. (2013) proposed a method that jointly operates itemset mining and multiple testing and applied their method to high-dimensional genetic data. Sugiyama et al. (2015) combined a graph mining approach with multiple testing. The novelty of my analysis is that the data are not obtained from experiments but instead from the actual purchase of care services. This data property requires us to eliminate spurious correlations. Then, I use a regression approach to examine the conditional relationships given the observable factors.

A directly related study is that of Sugawara et al. (2018), who combined a basket analysis and an econometric analysis in two-part models of medical expenditures. In their model, multiple service combinations appear as dependent variables. On the other hand, in this research, combined services appear as explanatory variables.

For regressions on high-dimensional data, there are two methodologies closely related to the analysis presented here. First, a reduced-rank regression (Izenman 1975) is a pioneering approach that considers grouped explanatory variables and their combined effects in the context of the regression. However, the scope of this approach differs from that of this current study because the reduced-rank regression handles a multivariate dependent variable. Second, the group lasso (Yuan and Lin 2006) is an approach used to estimate the shrinkage of grouped variables. However, as I discuss in a later section, the group lasso method has a different purpose compared with the method employed here. To obtain empirical interpretation from the estimation results, my method is more informative for my research purposes.

An analysis of long-term care service combinations in Japan is important in its own right as an empirical study. For Japanese LTCI, the existence of agency problems by gatekeepers has been reported by Sugawara and Nakamura (2016) and Iizuka et al. (2017). Here, providing accurate information on the correlation between services and health status can help to reduce information gaps between gatekeepers and consumers. Furthermore, although the coverage for many services is a distinct property of Japanese LTCI, previous studies on the demand for long-term care have focused on specific services (Noguchi and Shimizutani 2009; Sugawara 2017) or on aggregate demand (Hashimoto et al. 2010; Hanaoka and Norton 2008). On the other hand, this study considers detailed care plans, which have broad implications in terms of providing feasible and effective long-term care in Japan.

2 Japanese long-term care

2.1 Background

In response to the nation's rapidly aging population, the Japanese government established the LTCI in 2000.[2] The program is mandatory social insurance providing universal coverage of 90% of formal long-term care expenses. Because LTCI covers in-kind benefits only, its launch caused the emergence of new markets for various formal elderly care services including institutional care and home care. Compared with social insurance for long-term care in other countries, such as Germany and Korea, the Japanese program offers a wider range of coverage for moderate disabilities including various services related to at-home care.

To guide consumers in these new and complicated markets, the LTCI introduced coordinators, called care managers, who coordinate between consumers and service providers. Care managers create a *care plan*, which determines the type and amount of services and providers for each LTCI user. However, because care managers refer patients to providers, care managers can be a source of agency problems. Examples of empirical studies on the agency problem caused by care managers include the works of Sugawara and Nakamura (2016), who indicated the existence of supplier-induced demand by care managers, and Iizuka et al. (2017), whose finding implied the existence of selective referrals. Because the agency problem is caused by asymmetric information between users and care managers, providing information about efficient care plans can reduce the information gap and help to achieve better service choices.

2.2 At-home care services

The LTCI covers three categories of services: institutional, home-based, and community-based care. I eliminate institutional care from the analysis because

[2] For general information on Japanese LTCI, Ikegami and Campbell (2000) describe the original LTCI, and Tamiya et al. (2011) present a comprehensive review of the overall LTCI system.

such services are designed to be self-contained within a facility. The definitions of home-based care and community-based care are complicated. In this research, I select services that fall under the category of at-home care. Specifically, I eliminate community-based nursing homes, for-profit nursing homes, and group homes, which are categorized as home-based or community-based care but function more like institutional care, as discussed in Nakanishi et al. (2014). Additionally, I eliminate two services (equipment trade and home modifications for at-home care) from my empirical analysis because the claims data do not include information on these services.

As a result, at-home care in my data cover 14 services: (1) home care; (2) home bathing care; (3) home health care; (4) home care rehabilitation ; (5) day care; (6) outpatient rehabilitation; (7) equipment rental; (8) home care management and guidance; (9) night home care; (10) day care for the demented; (11) small-scale, multi-functional home-based care; (12) regular home visitation and as-needed visitation services; (13) nursing for small-scale, multi-functional home care; and (14) short stay.

Service (14), short stay, includes services at several types of facilities, such as non-profit nursing homes, long-term health care facilities, and specific facilities for short-stay care. Because the service offerings are the same, I do not consider separate services at these facilities.

In addition to regular care services, the Japanese LTCI covers preventive care for lighter care needs. Among the above services for at-home care, services (1)–(8) and (10)–(11), equipment trade and home modifications, have counterparts in the preventive care sector. Because the beneficiaries of regular and preventive care are not the same, I do not consider preventive care in this study but focus on regular care services.

I classify the above 14 at-home care services based on two criteria. The first criterion is whether a user receives a service at home or visits a facility. Services (1)–(4), (8), (9), and (12) belong to the at-home services category, whereas services (5), (6), (10), and (14) belong to the facility-based service group. As an example of the at-home category, (1) home care refers to a care service for which a caregiver visits the home of an elderly person to provide physical care and housekeeping support. As an example of the facility-based career category, (2) day care is a service for which a facility provides care and functional training for the elderly during the day including a pickup service. Services (11) and (13) are a mixture of these two categories, and (7) equipment rental is not classified in either category.

The second criterion is related to the service provider. Services (3), (4), (6), (8), and (13) are operated by providers with a medical background while services (1), (2), (5), (7), (9), (10), (11), and (12) are operated by providers who specialize in long-term care. Service (14), short stay, can be provided either by medical or long-term care providers. For the former category, similar services are also provided by hospitals through health insurance. However, there are several clear distinctions between the services provided under health and long-term care insurance.

For example, rehabilitation services (4 and 6) are provided by rehabilitation specialists, occupational therapists, physical therapists, or speech therapists.[3] There is also a requirement for contracting doctors to operate these services. Service (3), home health care, is a nursing care service provided by nursing staff, a doctor, dentist, dental hygienist, pharmacist, registered dietitian, nurse, practical nurse, or public health nurse. Service (8), home care management, is an advisory service, not accompanied by direct treatment, and is provided by doctors, dentists, or pharmacists.

3 The basket regression method

3.1 Problem setting

The sample is composed of N individuals. The dependent variable y_i measures the health outcome of individual i. In this research, I use the transition of a person's health status after using a care service as the dependent variable. In addition, I define the following vector notation, $\boldsymbol{y} = (y_1, \dots, y_n)'$.

I denote J as the number of care services. $\boldsymbol{d}_i$ is the J-dimensional vector of dummy variables for the care service use, in which an element d_{ij} is unity if the ith individual uses the jth service. I further assume that there are observable characteristics that might affect health status other than the use of long-term care services. These elements are represented by a p-dimensional vector, z_i.

To estimate the correlation between care service use and y_i, an intuitive approach is to regress y_i on $\boldsymbol{d}_i$ and z_i. Although this approach captures the coefficient of J services separately, multiple care service combinations typically have a more complicated relationship with a person's health status. This fact is confirmed in the Japanese context by the empirical analysis presented in later sections.

To analyze the relationship between multiple care services and health status, I face the problem of high-dimensionality in the sense that the number of combinations 2^J grows significantly with the number of services J. Because of the increasing availability of detailed medical or long-term care claims data, I have greater access to data with large J within health economics. Thus, the consideration of this high-dimensional problem might provide important policy implications.

3.2 A basket regression method

Note that to focus on the analysis of the high-dimensionality problem, I omit the subscript i hereafter when it is not strictly necessary.

I analyze the correlation between combined care and health status using a traditional regression analysis with dummy interaction terms. For example, the combination of services 1, 2, and 4 is represented by the cross-dummy variable $d_1 d_2 d_4$. As a result of the high-dimensionality problem, the possible number of explanatory

[3] Short-term use (1–2 h) of outpatient rehabilitation can also be provided by nurses, judo therapists, or licensed masseurs (*Amma Massaji Shiatsushi*).

variables can be large. However, for many of these cross-dummies, the corresponding coefficients are not strongly identified because $\boldsymbol{d}_i$ is typically sparse or includes many non-purchases in the actual purchase data.

To handle the high-dimensionality problem, my regression approach includes an additional step to reduce the number of dimensions using an itemset mining method. This step selects care services jointly used by a sufficient number of the elderly. I include only those itemsets that are selected in the first step as explanatory variables for the regression analysis. For the itemset mining method, I use the basket analysis approach of Sugawara et al. (2018), who analyze high-dimensional data for medical expenditures. I call this *basket regression*.

The basket analysis employs the following top-down algorithm, where itemset mining begins with the largest number of elements for combinations J and moves to smaller numbers.

Basket analysis algorithm

- Selection of a basket with J services: if there are τ or more elders with $(d_1, \dots, d_J) = (1, \dots, 1)$, then $\{1, \dots, J\}$ is a valid basket. I eliminate individuals who belong to this basket from the subsequent basket analysis.
- Selection for baskets with $J - 1$ services: if there are τ or more elders with $(d_1, \dots, d_J) = (-, 1, \dots, 1), (1, -, 1, \dots, 1)$,..., $(1, \dots, 1, -)$, then $\{2, 3, \dots, J\}$, $\{1, 3, 4, \dots, J\}$, ⋯, $\{1, 2, \dots, J - 1\}$ are valid baskets, respectively. I eliminate individuals who belong to this basket from the subsequent basket analysis.
- Selection for baskets with $J - 2$ services...selection for baskets with 1 services in the same manner
- Selection for a basket with 0 service: any remaining elders are allocated to an empty basket $(d_1, \dots, d_J) = (-, \cdots, -)$.

In the above algorithm, τ is a threshold value used to determine whether an itemset is a basket. This value is specified by the researcher. $-$ takes values in $\{0, 1\}$. When $\{b_1, \dots, b_B\}$ is a basket, the cross-dummy variable $d_{b_1} \dots d_{b_B}$ is included as an explanatory variable in the basket regression with $\beta_{b_1,\dots,b_B}$ as the corresponding regression coefficient.

As a result of my algorithm, there can be elders who belong to multiple baskets. For example, consider a situation in which individual i uses services 1, 2, and 3. Furthermore, $\{1, 2, 3\}$ is not a valid basket, but $\{1, 2\}$ and $\{2, 3\}$ are both valid baskets. In this situation, I assign individual i to two baskets: $\{1, 2\}$ and $\{2, 3\}$.

3.3 Interpretation of basket regression results

Although my basket regression is a simple method, it provides several possibilities for correlation analysis between multiple care service combinations and health status. When including a basket composed of many services, I also include nested baskets with a smaller number of services as explanatory variables. As a result, I use a single regression result to obtain three types of care service "effects."

First, I interpret a coefficient of a cross-dummy as an *interaction effect* in addition to baskets of smaller combinations. For example, if $d_1 d_2$ is included in the explanatory variables because the combination of services 1 and 2 is identified as a basket, I also include d_1 and d_2 as explanatory variables (if they are also baskets). Then, $\beta_{1,2}$, the corresponding regression coefficient for the cross-dummy, is an additional term for this combination after controlling for services 1 and 2.

Second, I analyze the *joint effects* of a combination of services by summing the coefficient estimates for all related baskets. For example, I measure the joint effects of $\{1, 2\}$ as $\beta_1 + \beta_2 + \beta_{1,2}$. The significance of the joint effects is testable using F-statistics for the linear constraints on the regression coefficients owing to my specification of the linear regression model.

Third, I analyze the *additional effect* of a care service using similar F-statistics. For example, suppose I am interested in the effects of $\{1\}$ in addition to those of basket $\{2, 3\}$. Here, I need to estimate $\beta_1 + \beta_{1,2} + \beta_{1,3} + \beta_{1,2,3}$. A typical misunderstanding of this situation is to measure this additional effect by $\beta_1 + \beta_{1,2,3}$. This is not correct because, in addition to the synergy effects of $\{1\}$ with $\{2, 3\}$, I must consider the synergy effects of $\{1\}$ with $\{2\}$ and $\{1\}$ with $\{3\}$ measured using $\beta_{1,2}$ and $\beta_{1,3}$.

To understand the properties of the additional effect, consider a situation where all baskets have a moderate positive correlation with health status except for basket $\{1, 2\}$, which has a serious side effect. An analysis of service 1, in addition to that of $\{2, 3\}$, must include the negative side effect measured by $\beta_{1,2}$. However, the coefficient $\beta_{1,2,3}$ does not capture this side effect because $\beta_{1,2,3}$ reflects a conditional correlation only of the combination $\{1, 2, 3\}$ given the nested baskets, which includes basket $\{1, 2\}$. Thus, including $\beta_{1,2}$ in the additional effect is an essential part of this analysis.

Note that not all nested itemsets are baskets. For example, even if $\{1, 2\}$ is a basket, d_1 is not a basket when there are fewer than τ users who use 1 on its own. This rule is required to avoid a multicollinearity problem. For example, if $\{1\}$ is automatically identified as a basket if $\{1, 2\}$ is a basket, then all users of basket $\{1\}$ are also users of $\{1, 2\}$. In this case, I cannot separately identify $\beta_{1,2}$ and β_1 because of multicollinearity.

The basic principle of the basket regression approach is to select the valid itemsets in the data and then employ regression analysis. Several previous methods perform a regression estimation and choose valid explanatory variables at the same time, such as the lasso (Tibshirani 1996) and the group lasso (Yuan and Lin 2006) approaches. Using these approaches, high dimensionality is not a serious problem because those combinations of services with a small number of users are automatically eliminated from the list of explanatory variables.

However, this type of shrinkage estimator does not provide a reasonable interpretation in the context of this study, which is aimed at estimating the effects of care services. For example, consider a situation where $d_1 d_2$ is an explanatory variable but d_1 is eliminated by the shrinkage. In the shrinkage estimation, I cannot say that the coefficient of $d_1 d_2$ represents the synergy effects of the combination because I do not control the nested basket. Therefore, in my problem setting, basket regression provides a more natural interpretation of the effects of a combination of services.

3.4 Choice of τ

An appropriate choice of τ is not straightforward. Because the value of τ determines the care service combination included as explanatory variables, the choice of τ is related to model selection. In general, model selection problems have two perspectives, goodness of fit and prediction precision. An apparently natural solution is to adopt model selection criteria that consider both perspectives.

On the other hand, the main purpose of this study is to estimate the regression coefficients of the relevant baskets and not to pursue the best statistical model and prediction precision. As such, an alternative, simple strategy exists where I concentrate only on the goodness of fit. Using this strategy, a smaller value of τ is a better choice because this enables a greater number of itemsets to be included as baskets. However, if the number of individuals using a combination of services is small, the degrees of freedom to estimate the coefficient of the combination become small creating difficulty in identifying the corresponding coefficient.

In this research, I adopt two strategies for the choice of τ. My primary approach is based on the simple strategy with small τ. Because there is no clear way to determine the appropriate degrees of freedom in this setting, I consider an ad-hoc value, 0.03% of the sample size, which seems to be sufficiently small for my empirical analysis. However, because this is not a general choice, I also perform a robustness check using different values of τ. My second approach adopts a model selection between models with different values of τ. Because my method is based on regression, I use adjusted R^2 as a model selection criterion.

3.5 Application to claims data

To apply my method to claims data, we need to consider the fact that the data are not derived from a randomized clinical control. For my purposes, it is difficult to find an appropriate experimental situation with randomized assignment.[4] The non-experimental property of the data yields three practical problems. The first problem is related to support for the realized combinations. For actual purchase data, many service combinations are seldom used. Such combinations, with a small number of users, do not form baskets, which means their relationship to health status cannot be analyzed using basket regression. This situation is different to that of experimental studies, where all possible options are allocated.

A justification for this problem is that people do not demand many care services at once, as shown in Sugawara et al. (2018) for medical care and in a later empirical study for long-term care. This study uses big claims data, which include 80% of long-term care users in Japan. Therefore, I consider this a general property of actual Japanese long-term care purchases.

The second and third problems are related to a general claims data problem in that they contain limited information on individual characteristics z. For example,

[4] An example of a study using an experimental situation for Japanese long-term care is Iizuka et al. (2017).

the claims data for Japanese long-term care include only age, gender, and care-need levels as individual characteristics. Given this limited availability of explanatory variables, the second problem arises as possible simultaneity bias. The bias is caused by reverse causality resulting from missing details on a person's health status, such as the status of an illness. For example, if a service combination is suitable for a transition to poor health status with respect to a specific illness, I can say that the health status affects the choice of services and, thus, causality is reversed.

To avoid this simultaneity problem, I construct the dependent variable using the health status transition 3 months later. The introduction of a time lag between the time a service is used and the time of an individual's health status evaluation can help to avoid the simultaneity problem. However, this approach might generate a new problem in that I cannot control the influence of a service used one or 2 months before the time of the health evaluation. Therefore, I perform an estimation using the transition 1 month later to check the robustness of the results.

The third and more serious problem is omitted variable bias. When both the choice of services and health status depend on an unobserved variable, endogeneity bias arises. For example, there is a possibility that an expensive service combination could be purchased only by wealthy users, and income affects the availability of health-related consumption. However, I do not observe individual income in my dataset. Because claims data are created from medical records, there is a general tendency whereby claims data do not contain detailed individual characteristics. Thus, omitted variable bias is a common difficulty for claims data analysis.

This study employs fixed effect analysis. As shown in the standard econometric textbook, such as Angrist and Pischke (2008, Ch.4), fixed effect estimation is an approach used to eliminate omitted variable bias if there is potential correlation between omitted variables. Another popular way to manage omitted variable bias is the instrumental variable method as adopted in Guo et al. (2015). However, the difficulty is that the high-dimensional component appears as an endogenous variable in my situation. In contrast, many previous studies, such as Stock and Yogo (2005), have analyzed situations with high-dimensional instruments. To control for many endogenous variables, the rank condition for identification requires that I have more instruments than I do endogenous variables, although claims data suffer from a lack of observable exogenous variables. Moreover, as Sugawara et al. (2018) show, even under a distributional assumption, the construction of a Heckit-type estimation method is not easy. This is because the choice model for service combinations is complicated because individuals belong to multiple baskets.

4 Data

4.1 Sample definition

The claims data for the empirical analysis are taken from the Survey of Long-term Care Benefit Expenditures conducted by the Ministry of Health, Labour and Welfare. The data include claims from over 90% of Japanese municipalities. The remaining municipalities do not permit the use of secondary data. As a result, the data include more than 80% of all LTCI users. Although the LTCI also covers those between the ages of 40 and 64 years who have an age-related disease, I focus on the elderly (i.e., individuals who are at least 65 years old).

Because care plans are created each month, the claims data compose monthly panel data of individual users. I obtain monthly claims for the period May 2006 to April 2015. Because there is a time lag between the use of a service and the recording of a claim, I restrict the study period to 6 months prior to the last recorded data (i.e., to November 2014).

The raw claims data have more than 500 million observations per month. To handle such volumes of large data, I choose a 1% random sample of individual—month observations, in which the individual uses at least one at-home service during the month.[5] Therefore, it is possible that the same people appear multiple times. However, because the number of observable months is 120, the expected number of times a person appears is at most 1.2 in the 1% random sample. Therefore, I do not incorporate individual fixed effects for this dataset. In other words, my main empirical analysis is employed for cross-sectional data rather than panel data.

4.2 Dependent and explanatory variables

The dependent variable is defined as the transition of a person's health status after using long-term care services. As mentioned in Sect. 3.5, I define a transition in health status as occurring 3 months after using a service to avoid the simultaneity problem. I also consider health status transition after 1 month as a robustness check.

For health transition, I incorporate a dummy variable that takes the value zero if health status worsens and one if the status is unchanged or improves. I call this dependent variable the outcome dummy. Although this dependent variable is discrete, I use a linear regression framework for simplicity. This is because my main interest is estimation and testing rather than prediction. For the robustness check, I include a more detailed dependent variable, which is outcome score. The outcome score takes the value zero if the person's health status worsens, one if the status is unchanged, and two if the status improves. These two dependent variables are also used in Iizuka et al. (2017). Additionally, I employ logistic regression in the robustness check.

For health status definition, I use the care-need level for LTCI. The care-need level is defined based on the time required for long-term care (Tsutsui and Muramatsu 2005). The use of these levels as a measure of health status is justified by Kurimori et al. (2006), who show that the levels correspond to appropriate quality of life measures. For my study period, there are seven care-need levels: assistance-required (AR) 1 and 2 and care-required (CR) 1 to 5, where the latter represents severe disability. Users who have an AR level can only use preventive care services while those who have a CR level can use regular services only. As mentioned in Sect. 2.2, I focus on the users of regular services who have a CR level.

[5] The data are stored in separate files for claims and care-need levels. Thus, it is too burdensome to merge data from these files if I include all observations.

An update of the assessed care-need level occurs in two ways: mandatory checkup or upon a user's request, which can be done at any time. For the mandatory checkup, the schedule is determined at the time of the assessment. The LTCI sets two standard schedules depending on the assessment. First, 6 months is recommended for a new assessment where assessment by user's request or assessment by mandatory update changes care-need categories from AR to CR or CR to AR, Second, 12 months is recommended for assessment by mandatory update without a change in AR or CR categories. Besides, the assessment committee can set a schedule that differs from the standard.

Considering the property of the update rule for care-need levels, I employ an additional analysis for the robustness check using the health transition 12 months later, which reflects the updated care-need level for most of the cases.

The transitions to death and to hospitals are treated as transitions to a worse state, regardless of the care-need level at time t. In contrast, a transition from CR to AR is treated as a transition to a better status. Any other type of attrition is treated as missing. Attrition may include transitions to a state without a care-need level, which can include transitions to a better status (e.g., a healthy status) or to a worse status (e.g., end-of-life home care), or moving to a different municipality. I cannot separately observe these reasons for attrition.

My model includes z, which are explanatory variables other than long-term care services. I include gender, age, and the care-need level as characteristics of individual users. For gender, a male dummy takes the value one if an individual is male, and zero otherwise. For the age-related variables, I use the logarithm of a user's age minus 64. Because the sample includes only those who are at least 65 years old, this log-transformed variable takes a non-negative value. I also include the squared value of the logarithm of the age variable. For care-need level, I include dummy variables CR2, CR3, CR4, and CR5 to denote the level at time t. Here, CR1 is eliminated as a reference category. I also adopt dummy variables for prefecture and year to control for regional differences and time trends, respectively.

The upper part of Table 1 shows the descriptive statistics for the dependent variables and the explanatory variables other than long-term care services. To show the characteristics of the data in the empirical analysis, I eliminate observations belonging to an empty basket, which is defined later. For the dependent variables, because the outcome dummy has 0.93 as its mean, transitions to a worse health status occur for 7% of the elderly.

I find a small difference between the outcome dummy and the outcome score. This finding indicates that only a small number of the elderly improve their health status. In other words, most of the elderly for whom the outcome dummy is one show unchanged care-need levels.

For the independent variables, it is natural that the data for the elderly include a higher proportion of females because females live longer, in general. For care-need levels, the number of elderly an each level is inversely proportional to the level. This is also a natural finding because home care is designed mainly to treat those who require less care. Those who need more care are likely to move to institutional care, even under the Japanese LTCI.

Table 1 Descriptive statistics for independent and dependent variables

		Mean	S.D
Dependent variables	Outcome dummy	0.930	0.256
	Outcome score	0.965	0.324
Independent variables	Male	0.326	0.469
	Age	83.205	7.565
Care-need level (%)	CR1	0.316	0.465
	CR2	0.289	0.454
	CR3	0.192	0.394
	CR4	0.123	0.329
	CR5	0.079	0.270
Care services			
Index		# Users	% Use
1	Home care	609,872	36.643
2	Home bathing care	56,769	3.411
3	Home health care	188,280	11.312
4	Home care rehabilitation	38,620	2.320
5	Day care	801,034	48.129
6	Outpatient rehabilitation	295,024	17.726
7	Equipment rental	780,494	46.894
8	Home care management and guidance	223,537	13.431
9	Night home care	3,319	0.199
10	Day care for the demented	40,179	2.414
11	Small-scale multi-functional home-based care	33,535	2.015
12	Regular home visitation and as-needed visitation services	786	0.047
13	Nursing small-scale multi-functional home care	206	0.012
14	Short stay	256,766	15.427
N	1,664,362		

The lower part of Table 1 shows the numbers and percentages of elderly who use each care service. As shown, the major categories of care services are (1) home care, (5) day care, and (7) equipment rental, each of which are used by more than 30% of users. I also find that (13) nursing for small-scale, multi-functional home care has only 206 users. Here, I set $\tau = 500$ as the threshold value for my empirical analysis. Because the number of users is smaller than τ, this service cannot be an element of any basket.

4.3 Alternative samples for additional analysis

In addition to my main data defined above, I construct two alternative samples for additional analysis. The first alternative sample is a subsample of the main data. Here, I focus on the subsample of users who are not new fpr the LTCI in the sense that they have experienced three or more months of LTCI services since their first use. To define this subsample, I eliminate elderly individuals who are recorded from the first wave of the data, May 2006, because I cannot tell whether they are new users at this wave. Consequently, my subsample is composed of 824,347 elderly individuals.

The second alternative sample is panel data to employ the fixed effect analysis, as mentioned in Sect. 3.5. To construct a panel dataset, I further conduct 10% random sampling on individuals from the main data defined above. The proportion of random sampling is selected to obtain a similar sample number of observations as the main data to adopt the same value of τ without further discussion. To focus on health transition 3 months later, I construct quarterly panel data composed of observations for January, April, July, and October. The resulting data are an unbalanced panel composed of 162,003 elderly individuals and 2,300,463 observations.

Although the fixed effect model is useful to eliminate the omitted variable bias, I do not adopt the panel data analysis for my main analysis for two reasons. The first reason is related to the property of the update schedule, which is described in the previous subsection. Because the care-need levels remain the same for several months, it is likely that I will observe similar patterns of health transition and expenditures during these months. Thus, cross-sectional data can provide more variety in care service use patterns to detect baskets, or frequently purchased itemsets, compared to panel data. To model such a property of the update schedule, we need to adopt a dynamic panel approach with autoregressive terms. However, this approach is beyond the scope of this research.

The second reason is difficulty in interpretation. My original basket regression specification does not include a constant term in the regressors but includes dummy variables that correspond to all baskets. Thus, to adopt fixed effects into this framework without a multicollinearity problem, I specify a reference basket whose interaction effect is eliminated from the regressors. In choosing a reference basket, if I eliminate a basket, it affects the joint effect for all baskets including the eliminated basket. Thus, it is problematic to eliminate a low-dimensional basket. Hence, I eliminate a basket with the highest dimension. However, because of this operation, the joint and additional effects under the fixed effect model are not simple to interpret because of the existence of the reference category and fixed effects.

5 Empirical analysis

5.1 Preliminary regression analysis

I begin my empirical research with a preliminary regression analysis that includes dummy variables only for the use of each service, not for their combinations, as explanatory variables. This analysis indicates what I can learn without considering care service combinations. I use the same sample as that of basket regression to make a clear comparison. Specifically, I eliminate observations belonging to the empty basket, which is defined in the next subsection.

Table 2 Results of preliminary regression. Robust standard errors are in parentheses. Dummy variables for years and prefectures are included as explanatory variables but abbreviated. $***$ for $p < 0.01$

			Coef.	S.E.
z		Male	0.0039	(0.003)
		Log age	0.5101***	(0.086)
		Squared log age	−0.1007***	(0.016)
	Care-need level	CR2	0.0502***	(0.004)
		CR3	0.0662***	(0.004)
		CR4	0.0901***	(0.003)
		CR5	0.1351***	(0.004)
d	Use of service (d)	1 Home care	0.0213***	(0.004)
		2 Home bathing care	−0.0199***	(0.003)
		3 Home health care	−0.0050***	(0.002)
		4 Home care rehabilitation	0.0118***	(0.002)
		5 Day care	0.0210***	(0.004)
		6 Outpatient rehabilitation	0.0366***	(0.005)
		7 Equipment rental	−0.0124***	(0.001)
		8 Home care management	−0.0100***	(0.002)
		9 Night home care	−0.0227***	(0.007)
		10 Day care for the demented	−0.0155***	(0.004)
		11 Multi-functional care	−0.0088**	(0.004)
		12 Regular home visitation	0.0070	(0.009)
		13 Nursing multi-functional care	−0.0425	(0.030)
		14 Short stay	−0.0279***	(0.001)
Observations			1,664,362	

Table 2 shows the estimation results for this preliminary analysis. In this estimation, the dependent variable is the outcome dummy. The explanatory variables do not contain combinations of services but only dummy variables on the use of each service $(d_1, \ldots, d_{14})$ and the other explanatory variables z. I also adopt dummy variables for prefectures and years to control for regional difference and time trends, respectively, but these coefficient estimates are abbreviated. I do not include a constant term as an explanatory variable. Consequently, the estimated coefficients of the dummy variables can be interpreted as the absolute correlation between the service and health status.

Of the 14 services, four show significant and positive coefficients, and eight show significant and negative coefficients. It is difficult to provide a natural interpretation for these results. This result, along with those for the basket analysis with interpretable insights, shows that combinations of services need to be considered when analyzing home care for the elderly in Japan.

For the coefficients of the explanatory variables other than care services, I find a nonlinear relationship between age and health status from the positive coefficient for age and the negative coefficient for its squared value. For the coefficients

Table 3 Popular baskets used by more than 50,000 elderly individuals. 1 home care, 2 home bathing care, 3 home health care, 4 home care rehabilitation, 5 day care, 6 outpatient rehabilitation, 7 equipment rental, 8 home care management and guidance, 9 night home care, 10 day care for the demented, 11 small-scale, multi-functional home-based care, 12 regular home visitation and as-needed visitation services, 13 nursing for small-scale, multi-functional home care and 14 short stay

(1) Service ID			(2) # Elderly individuals	(3) Joint effects
5			252,902	0.7778
5	7		118,516	0.7569
1			115,231	0.7878
8			89,274	0.7421
1	5		86,688	0.7739
6			73,733	0.7866
7			70,773	0.7627
1	7		70,474	0.7573
1	5	7	68,263	0.7505
6	7		58,361	0.7694
5	14		51,136	0.7382

of the care-need levels, the table shows that heavier care-need levels are associated with larger positive coefficients. This relationship between health transitions and care-need levels is consistent with the findings of previous studies, such as Iizuka et al. (2017).

5.2 Results of the basket analysis

This subsection reports the results of the basket analysis, which is the first step of the basket regression method. I adopt $\tau = 500$, which is approximately 0.03% of my sample. From the basket analysis, I obtain an empty basket with 191 of the elderly whose services do not compose a basket. I eliminate those who belong to this empty basket from the sample for regression analysis because I do not have sufficient observations to analyze the empty basket.

Other than the empty basket, I obtain 199 baskets. This finding implies that only 1.22% (0.0122 = 200 / 16,384) of the service combinations are used by 0.03% of the elderly. In other words, the basket analysis successfully reduces the dimensions by selecting only valid baskets. However, the number of baskets is still too large to show the full empirical result table. Thus, I do not show all the results of the basket analysis and the basket regression.[6]

The result of the basket analysis shows that the largest dimension for baskets is six. I obtain five six-dimensional baskets, which include 4,988 individuals: $\{1, 2, 3, 4, 7, 8\}$, $\{1, 2, 3, 5, 7, 8\}$, $\{1, 2, 3, 7, 8, 14\}$, $\{1, 3, 5, 7, 8, 14\}$, and $\{1, 3, 6, 7, 8, 14\}$. In addition, for the five-, four-, three-, two- and one-dimensional baskets, I obtain 34, 49, 32, and 11 baskets, which include 39,988, 133,698, 310,799, 539,255, and 678,165 people, respectively. The services for (12) regular home visits and as-needed visitation services and (13) nursing small-scale, multi-functional home care are not part of any basket.

[6] A full table is available upon request.

Compared with the descriptive statistics for the use of each service in Table 1, service (7), equipment rental, is a major service in both tables. On the other hand, (1) home care and (5) day care, which are two major categories in terms of the number of users, show similar numbers of baskets to service (3) home health care and service(8) home care management and guidance, which are used by less than 15% of users. These findings indicate the popularity of medical services (3) and (8) as additional elements in creating multiple service care plans.

I show popular care plans used by more than 50,000 of the elderly in Table 3. Columns (1) and (2) of this table show the service IDs that compose the basket and the number of users, respectively. All combinations of the three major services (1, 5, and 7) are included in these popular care plans. Additionally, all of the popular care plans, except the two one-dimensional baskets, $\{6\}$ and $\{8\}$, include at least one of these major services. In summary, the major services are major elements of popular care plans.

This table also shows that there are only 11 baskets with more than 50,000 elderly (about 3% of the sample). Combining this with the previous finding of 199 valid baskets, I find that the Japanese LTCI has a moderate variety of care plans.

5.3 Results from basket regression

Here, I show the main results of the basket regression. As in the previous analysis of the preliminary regression, I do not include a constant term in the regression analysis and eliminate the elderly who use the empty basket.

For all 199 baskets, excluding the empty basket, the estimated joint effects are significant and positive. This is a more reasonable result than that of the preliminary regression, which found both a negative and positive correlation between care services and health status. Based on this result, I calculate the average joint effect of all care plans as a weighted average of these joint effects, for which the weights are the ratios of users for each care plan. The estimate for the average joint effect is 0.756.[7] Because I employ a linear regression analysis, this estimate implies that the probability of maintaining or improving the care-need level increases by 76% points for an average care plan.

Next, to detect distinctive care plans with a high and low correlation with health status, I conduct F-tests for the null hypothesis that the joint effect of a care plan is different from this average. Table 4 shows the number of baskets with 1% and 10% significant differences in the joint effects against the average. For each service, I count the number of baskets, which include the service, with larger joint effects than average (better than average) and with smaller joint effects than average (worse than average). In the 1% level, the number of better-than-average baskets is larger than the number of worse-than-average baskets for (3) home health care, (4) home care rehabilitation, (6) outpatient rehabilitation, and (8) home care management and

7 I also find that the simple average of the joint effects for all 199 baskets is 0.743. The small difference between the simple and the weighted average implies that the joint effects for care plans are generally similar.

Table 4 Number of baskets with 1% and 10% significant difference in the joint effect compared with the average including each service

Service	# Baskets, against average			
	1% level		10% level	
	Better	Worse	Better	Worse
1 Home care	2	5	4	28
2 Home bathing care	2	3	3	18
3 Home health care	7	5	7	24
4 Home care rehabilitation	4	1	5	6
5 Day care	0	4	2	10
6 Outpatient rehabilitation	5	4	7	6
7 Equipment rental	0	4	0	37
8 Home care management	7	6	8	22
9 Night home care	0	0	0	0
10 Day care for demented	3	6	3	11
11 Multi-functional care	0	2	0	2
12 Regular home visitation	0	0	0	0
13 Nursing multi-functional care	0	0	0	0
14 Short stay	3	3	3	19

Table 5 Baskets with 1% significant difference between the joint effect and the average

Better than average					Worse than average					
# Elders	Services			Joint effects	# Elders	Services				Joint effects
976	8	10		1.2558	3097	2				0.4499
644	6	10		1.062	1911	4				0.575
601	3	10		1.0233	646	3	5	6		0.5955
500	4	8		1.0166	531	5	6	8		0.6277
1146	6	8		0.9586	864	1	10	14		0.6397
830	4	6		0.9393	588	7	8	10	14	0.6405
557	3	8	14	0.9118	642	3	7	8	10	0.6438
553	3	6	14	0.8803	683	1	5	10		0.648
507	3	4	8	0.8734	979	5	10	14		0.6574
911	8	14		0.8617	834	1	7	8	10	0.6728
2038	1	4		0.841	723	3	6	8		0.6729
569	2	3	8	0.8353	1452	1	6	8		0.6731
672	1	2	3	0.8349	10,366	3				0.6777
1837	3	6		0.826	1168	1	2			0.6904
					4762	2	3	7		0.6918

1 Home care, 2 home bathing care, 3 home health care, 4 home care rehabilitation, 5 day care, 6 outpatient rehabilitation, 7 equipment rental, 8 home care management and guidance, 10 day care for the demented and 14 short stay

guidance. Of these five services, the last four services are operated by providers with a medical background.

At the 10% levels, for many services, the number of worse-than-average baskets is larger than the number of better-than-average baskets. The exception is (6) outpatient rehabilitation. I also find that (4) home care rehabilitation shows a moderate result in the sense that the difference between the number of worse-than-average and better-than-average is only one. At the 10% level, the number of better-than-average baskets is substantially smaller than the number of worse-than-average baskets. In this case, the main reason is that there are many worse-than-average baskets whose joint effects are similar to the average.

Table 5 shows the estimated joint effects of baskets with a 1 % significant difference from the average. I see that all of the baskets with a significantly larger joint effect than average include at least one medical service. As a result, I conclude overall that the care plans with medical services have a strong positive correlation with health status. These care plans are not included in the popular care plans in Table 3. More specifically, medical services are included in only three of the 11 popular care plans in Table 3, and services (3) and (4) are never included. As shown in column (3) of Table 3, all popular care plans show similar joint effects as the average. On the other hand, from Table 5, the basket composed of (8) and (10) shows 1.256 as the largest joint effect. This joint effect is five times larger than the average ($1.256/0.756 = 1.66$).

Table 5 also shows that many baskets with large joint effects are two dimensional. There are no four-dimensional (or more) baskets nor one-dimensional baskets with joint effects larger than average at the 1% level while there are several baskets with one or four dimensions for smaller joint effects than average at the 1% level. However, the results of the basket analysis show that the use of baskets with two services is limited to one-third of the elderly.

5.4 Elimination of potential bias

5.4.1 Controlling simultaneity bias

There is an alternative interpretation of the results shown in Tables 3 and 4 from the perspective of individual choice. Specifically, when the elderly who are more likely to maintain or improve their health status frequently choose the better-than-average baskets in Table 4, the result only reflects reverse causality. As mentioned in Sect. 3.5, I try to avoid this simultaneity problem by introducing time lags between the time when services are used and the time when health transitions are measured.

To consider a simultaneity problem in more detail, I conduct two additional analysis. First, the analysis of additional effects provides further evidence as follows.

Table 6 summarizes the additional effects of each service for popular care plans. Although I estimate all additional effects from all baskets, I only report the number of baskets for which the additional use of the service yields a significant additional effect at the 10% level. Table 6, shows that rehabilitation services, (4) home care rehabilitation, and (6) outpatient rehabilitation have, in many cases, a positive

Table 6 Additional effects on popular care plans

Base		5	5 7	1	8	1 5	6
Additional	1	−0.0039**	−0.0064***		0.0345***		0.0171***
	2		−0.0397***	−0.0974***			
	3	0.0081**	−0.0177***	−0.0053**	0.0041	−0.02***	0.0394***
	4	0.0398***	0.003	0.0532***	0.2745***	−0.0013	0.1527***
	5			−0.0139***	0.023***		0.0118***
	6	0.0206***	0.0058***	0.0159***	0.2165***	−0.0222***	
	7	−0.0209***		−0.0305***	−0.0119*	−0.0234***	−0.0172***
	8	−0.0127***	−0.0199***	−0.0112**		−0.03***	0.172***
	9			0.0001			
	10	0.0109	−0.0371***	−0.0069	0.5137***	−0.1259***	0.2754***
	11				−0.0103		
	14	−0.0396***	−0.0288***	−0.0433***	0.1196***	−0.0553***	−0.0289***

Table 6 (continued)

Base		7	1	1	6	5	10% Level	
			7	5	7	14	Positive	Negative
				7				
Additional	1	−0.0054**			−0.0033	−0.0196***	2	3
	2	−0.0547***	−0.0487***	−0.0291***	−0.0337***		0	6
	3	−0.036***	−0.0193***	−0.0153***	−0.023***	−0.0023	2	7
	4	−0.0005	−0.0073**	−0.0007	−0.0085*		4	2
	5	−0.0058***	−0.0068***		−0.0067***		2	4
	6	0.0067***	0.0088***	0.0065**		0.0134**	8	1
	7					−0.0101***	0	6
	8	−0.0325***	−0.0419***	−0.0175***	−0.0099*	0.0011	1	8
	9		−0.0192***	−0.0019			0	1
	10	−0.0256***	−0.0301***	−0.0379***	−0.0326***	−0.0808***	2	7
	11	−0.0413***					0	1
	14	−0.043***	−0.0459***	−0.0309***	−0.0295***		1	9

*** for $p < 0.01$, ** for $p < 0.05$ and * for $p < 0.1$. The lower right part reports the number of baskets with 10% significance for additional effects. 1 home care, 5 day care, 6 outpatient rehabilitation, 7 equipment rental, 8 home care management and guidance and 14 short stay

Table 7 Subsample result for not new users. Baskets with significantly different joint effects compared to the average

Worse than average					Better than average				
Joint effect	Services				Joint effect	Services			
0.1872***	2				0.4141***	4	8		
0.1899***	4				0.3873***	3	4		
0.2387***	1	6	14		0.3712***	6	8		
0.2447***	3				0.3434***	1	14		
0.2449**	5	10	14		0.3413***	3	8		
0.2474**	1	2			0.3396***	5	10		
0.2496**	3	4	7	8	0.3285***	1	10		
0.2502*	2	4	7	8	0.3272***	8	14		
0.2508**	1	2	4	7	0.3215**	4	5		
0.2598*	10				0.3195**	3	6		
					0.3181**	1	4		
					0.3136**	3	5		
					0.3085*	1	4	7	8
					0.3071**	5	8		
					0.3060**	10	14		
					0.3003*	5	8	14	

$***$ for $p < 0.01$, $**$ for $p < 0.05$, and $*$ for $p < 0.1$. 1 home care, 2 home bathing care, 3 home health care, 4 home care rehabilitation, 5 day care, 6 outpatient rehabilitation, 7 equipment rental, 8 home care management and guidance, 10 day care for the demented, and 14 short stay

additional effect on popular care plans. These results show that rehabilitation services have a positive correlation with health status not only for people experiencing a positive transition but also for the elderly population in general.

Second, I eliminate new users of LTCI. As mentioned in Iizuka et al. (2017), new users are more likely to improve their care-need levels than those who are not new to LTCI. At the same time, many elderly individuals begin to use LTCI services when they transition from hospital to home. In this transition stage, medical services are often used for integrated care provision. Thus, there is a possibility that users who are more likely to improve use medical services.

For basket analysis using the subsample of not-new users, I obtain 143 baskets including an empty basket. Using basket regression, the estimated average joint effect is 0.282. This is approximately one third of the average joint effect for the full sample, 0.756. The finding of such a small average effect for not-new users is a supporting evidence on the statement that new users are more likely to improve. For services (1), (3), (4), (5), (6), (8), (10), and (14), the number of better-than-average baskets is larger than the number of worse-than-average baskets. All medical services are included in this list of services as well as non-medical services (1), (5), (10), and (14).

On the other hand, Table 7 shows baskets with significantly different joint effects compared with the average in this subsample analysis. Among better-than-average

Table 8 Number of baskets with 10% significant difference in the joint effect compared to the average including each service, panel data with fixed effects

Service	10% level	
	Better	Worse
1 Home care	5	19
2 Home bating care	1	2
3 Home health care	7	7
4 Home care rehabilitation	7	1
5 Day care	8	12
6 Outpatient rehabilitation	7	2
7 Equipment rental	11	16
8 Home care management	4	8
9 Night home care	0	0
10 Day care for the demented	0	15
11 Multi-functional care	0	3
12 Regular home visitation	0	0
13 Nursing multi-functional care	0	0
14 Short-stay	2	19

baskets, four among five best baskets, (4, 8), (3, 4), (3, 8), and (6, 8) are composed of medical services only.

I summarize the above results as follows. My results indicate that the simultaneity problem might exist in my full sample analysis in the sense that the strongly positive joint effects of medical services are affected to a certain extent by new users. At the same time, even after eliminating new users, my analysis still implies that medical services have a positive correlation with health status.

5.4.2 Controlling omitted variable bias

As mentioned in Sect. 3.5, I employ a fixed effect analysis to eliminate omitted variable bias. For a reference category, I eliminate a basket $\{1, 3, 5, 7, 8, 14\}$ to which 2,763 individuals belong. This basket has the largest number of individuals among six dimensional baskets, which is the highest dimension obtained by the basket analysis. Note that we can estimate the joint effect for this eliminated basket by letting the interaction effect of this basket be zero. Because this model has the reference category and fixed effects, it is not simple to interpret the values of the joint effects. Instead, in this analysis, I focus on the difference compared to the average of joint effects.

Table 8 shows the number of baskets with significant difference in joint effects compared to the average under the fixed effect model. I only report results for the 10% significance level because there are only a small number of baskets that have a 1% significant difference against averages. The number of better-than-average baskets is seven for both (4) home care rehabilitation and (6) outpatient rehabilitation, respectively, while the number of worse-than-average baskets are one and two. As a result, even controlling for omitted variable bias, rehabilitation services have many baskets with a positive correlation to health status.

5.5 Discussion on rehabilitation services

The above empirical analysis shows that many care plans that include medical services, particularly rehabilitation services, have a positive correlation with health status. The importance of a successful combination of medical and long-term care is reported by previous studies in the context of integrated care between hospitalization and institutional long-term care (Johri et al. 2003). My empirical analysis provides results consistent with previous studies on at-home care.

For Japanese LCTI, there are two functions of care services, functional training of the recipient and life support including family support. The latter is not always designed to improve health status. The purpose of many services is a combination of these two functions while rehabilitation focuses more on functional training than other services. This is why rehabilitation is particularly effective in terms of health status improvement.

On the other hand, I show that the use of rehabilitation services is not popular in actual care management. Then a question arises; why are these services unpopular? For individual characteristics, it was reported that day care and outpatient rehabilitation are used by elders with similar characteristecs in their age and care-need levels in the documents for 2016 Social Security Council provided by Japanese Ministry

Table 9 Regional variations in service usage rates

Service		Mean	S.D.	Min	Max	Max/Min
1	Home care	0.343	0.072	0.225	0.546	2.42
2	Home bathing care	0.030	0.015	0.007	0.069	10.06
3	Home health care	0.103	0.027	0.055	0.166	3.02
4	Home care rehabilitation	0.024	0.010	0.007	0.052	7.86
5	Day care	0.501	0.060	0.387	0.639	1.65
6	Outpatient rehabilitation	0.192	0.052	0.095	0.345	3.61
7	Equipment rental	0.462	0.044	0.365	0.565	1.55
8	Home care management and guidance	0.103	0.045	0.038	0.258	6.85
9	Night home care	0.001	0.002	0.000	0.008	
10	Day care for the demented	0.024	0.011	0.009	0.053	5.64
11	Small-scale multi-functional home-based care	0.023	0.010	0.006	0.046	7.34
12	Regular home visitation and as-needed visitation services	0.000	0.000	0.000	0.002	
13	Nursing small-scale multi-functional home care	0.000	0.000	0.000	0.001	
14	Short stay	0.164	0.047	0.071	0.307	4.32
N		47				

I do not calculate the ratio of the regional maximum over the regional minimum for (9), (10), and (11) because there are several prefectures with no users for these services of Health, Labor and Welfare.[8] Thus, these characteristics may not be main reasons why rehabilitation services are not selected.

To provide a potential answer to the question, Table 9 shows regional variations in usage rates for each service. Regional descriptive statistics are recorded for 47 Japanese prefectures, which is the largest regional authority next to the central government. The table reports the regional mean, standard deviation, maximum and minimum values, and the ratio of the maximum to the minimum values. The ratio represents the difference in usage rates between a prefecture with the best accessibility and a prefecture with the worst accessibility to the service.

The table indicates the existence of regional variations in the usage rates among services. For the popular services, (1), (5) and (7), the ratio of maximum to minimum values is between 1 and 2.5. On the other hand, for medical services (3), (4), (6), and (8), the rates are between 3 and 8.

These variations are caused by regional disparities in service location. There may be several reasons for this uneven location. First, unlike the popular services, these medical services have strict requirements for providers with specialized medical skills, as mentioned in Sect. 2.2. Thus, it might be difficult to employ sufficient numbers of skilled workers in rural regions. Second, the regional demand for such specialized services might be limited in rural areas.

The existence of regional disparities in long-term care services has already been noted by Mitchell et al. (2008). The government has also recognized the problem and provides bonuses for firms that are located in scarce areas. However, such a policy has not completely solved the problem of regional disparity, and the use of rehabilitation services may be limited owing to regional disparities in accessibility.

5.6 Robustness check

To check the robustness of my results, I provide five additional analyses. I report the results for rehabilitation services in these analyses mainly for the first four specifications. First, I adopt a different dependent variable, as mentioned in Sect. 4.2. My main result is obtained using a dummy variable that treats the maintenance and improvement of care-needs equivalently. Here, I emphasize improvement. For this purpose, I use the outcome score, which takes the value zero if the health status worsens, one if the status is unchanged, and two if the status improves. In this analysis, the basket analysis is equivalent, because only the dependent variable changes. The numbers of better-than-average baskets are 13 and 20 for (4) home care rehabilitation and (6) outpatient rehabilitation, respectively, while the numbers of worse-than-average baskets are five and 12 at the 10% level.

Second, as I discussed in Sect. 3.4, the choice of the threshold value for the basket analysis is not a simple task. In this robustness check, I incorporate a different threshold value, $\tau = 1,000$. The basket analysis yields 149 valid baskets and an empty basket. It is natural that a larger threshold, which makes an itemset harder to be a basket, results in a smaller number of baskets. The numbers

[8] https://www.mhlw.go.jp/file/05-Shingikai-12601000-Seisakutoukatsukan-Sanjikanshitsu_Shakaihoshoutantou/0000135320.pdf, accessed October 3, 2019.

of better-than-average baskets are three and 11 for (4) home care rehabilitation and (6) outpatient rehabilitation, respectively, whereas the number of worse-than-average baskets is two and nine, respectively, at the 10% level. Additionally, the adjusted R^2 for $\tau = 500$ and $\tau = 1,000$ are 0.9294 and 0.9280, respectively. Thus, $\tau = 500$ is preferred for model selection using the adjusted R^2.

Third, as mentioned in Sect. 3.5, I analyze the health transition 1 month later to control the influence of later inputs instead of 3 months later as in my basic analysis. For the robustness check, I also perform basket analysis because the sample is different from my original owing to attrition. As a result, the basket analysis reveals that the number of baskets is unchanged from the main analysis. The numbers of better-than-average baskets are 11 and 30 for (4) home care rehabilitation and (6) outpatient rehabilitation, respectively, while the numbers of worse-than-average baskets are three and six, respectively, at the 10% level.

Fourth, as mentioned in Sect. 3.5, I analyze health transition 12 months later to control timing of updates for care-need levels. The basket analysis yields 188 valid baskets and an empty basket. I observe a smaller number of individuals whose health transition is reported after 12 months rather than after 3 months. Thus, it is natural to obtain a smaller number of baskets.

Because the distribution of the joint effects is not symmetric, the number of better-than-average baskets is much larger than the number of worse-than-average baskets for all services. However, at both the 1% and 10% levels, the difference between these numbers show that (4) home care rehabilitation and (6) outpatient rehabilitation show a moderate result in the sense that the number of differences is smaller than they are for other popular services.

In summary, from the regression results from the above four specifications, rehabilitation services always have many baskets with a positive correlation to health status. Therefore, these results guarantee the robustness of my main analysis.

Fifth, as mentioned in Sect. 4.2, I employ logistic regression instead of linear regression in my main results. For this specification, I face a challenge in the application of the logit results on the inference of joint and additional effects. The interaction effects can be analyzed using the marginal effects of explanatory variables for the logistic regression. On the other hand, the joint and additional effects are defined as the sum of the marginal effects. This implies that these effects are the sum of the nonlinear functions of the coefficient estimates and, hence, it is difficult to obtain the closed-form expression for the test statistics. Considering this point, I concentrate on a discussion of the interaction effects in this robustness check.

Although I abbreviate the entire table to save space, the number of interaction effects at the 10% significant and with different signs under linear and logistic regression specifications is two over 140. Additionally, the number of interaction effects at the 10% significant level only for a specification and not significant at the 10% level for another specification is 18 over 59. These numbers imply consistent results from the two specifications.

6 Conclusion

This study has proposed a basket regression approach to estimate the effects of multiple care service combinations. My empirical analysis has shown that there are only 200 itemsets that are purchased by more than 0.03% of users among more than 16,000 combinations of Japanese long-term at-home care services. I have also shown that some medical and long-term care combinations are positively correlated with the health status of the elderly.

Although my statistical approach has the novelty of handling high-dimensional data for combined care services, my empirical analysis has five shortcomings. Two problems are because of a lack of data. First, I can analyze only limited consumer heterogeneity using claims data. In long-term care, an appropriate choice in services is more patient-specific than it is for medical care. For example, the presence of a co-resident family caregiver can decrease the demand for home care and increase the demand for day care. Because most claims data do not contain information on household characteristics, these notions are beyond the scope of studies based on claims data. This data limitation yields two problems. One problem is that I cannot control these unobserved elements as explanatory variables. The second problem is that I cannot adopt dependent variables other than health status. For example, I cannot analyze the care burden of family members.

Second, as summarized in Sect. 3.5, the data are not based on randomized clinical trials but on actual purchases. An important shortcoming is the possible endogeneity of care service choices. The choice of services might be correlated with unobserved individual characteristics such as income, which is also likely to affect health status. In this study, I do not consider the endogeneity problem because the estimation problem is already complicated without considering such a problem. Further studies in this field based on recent econometric achievement on high-dimensional treatment effect estimation, such as Belloni et al. (2017), must be meaningful.

Third, an important shortcoming of this study is that I do not analyze medical sectors because I have no access to information on health insurance claims. Considering my finding on the importance of medical care services to long-term care, future research using both medical and long-term care claims data would provide considerable implications.

Fourth, I cannot analyze health status, which is beyond the scope of care-need levels owing to the data. For example, my data contain only elders who are assigned some care-need level and do not always include clear information on the reasons for attrition, such as transitions from at-home care to institutional long-term care, hospital care, or death, as mentioned in Sect. 4.2. To tackle this problem, Fu and Noguchi (2019) recently provided an analysis of data created by data linkage on the claims data of Japanese LTCI and vital statistics to merge information on death. With such a detailed dataset, a more detailed analysis of health transition is possible.

In addition to the problems of limited data, I have a technical problem. The fifth problem is that the scope of this research depends on whether various treatment options are used, whereas claims data generally include information on the volume of used care as continuous variables. Thus, because the interaction of continuous variables is beyond the scope of the basket regression proposed here, it remains a future task.

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