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Abstract

A wave of new technologies – such as robotics, artificial intelligence, and digital platforms – prompts both concern about automation and unemployment as well as optimism about innovation enriching longer, healthier lives. In one of the first studies of service sector robotics using establishment-level data, we study the impact of robots on staffing in Japanese nursing homes, using geographic variation in robot subsidies as an instrumental variable. We find that robot adoption decreases difficulty in staff retention, as well as increases employment of care workers and nurses on flexible employment contracts. Our findings suggest that robots may help to remedy challenges posed by rapidly aging populations and strained caregiving workforces, and that their adoption may not be detrimental to workers or quality of care, although more research would be valuable.

JEL Code: I11, J14, J23, O30,
Key words: Robots, jobs, nursing homes, automation, aging, healthcare

* Corresponding author Eggleston: Freeman Spogli Institute for International Studies, Stanford University and NBER (karene@stanford.edu); Lee: University of Notre Dame; Iizuka: Department of Economics, University of Tokyo; Xi: Stanford University. We gratefully acknowledge financial support from the Freeman Spogli Institute for International Studies Japan Fund, and JSPS KAKENHI Grant Number 18H00861. We thank discussants including Robert Seamans at the AEA 2020 meetings and seminar participants at Stanford University Human-Centered AI Institute, SIEPR, and NBER Summer Institute 2020. Sean Chen, Haruka Ito, Greta Bollyky and Sophia Li provided excellent research assistance.

A wave of new technologies – such as robotics, artificial intelligence, and digital platforms – prompts both concern about automation and unemployment as well as optimism about innovation enriching longer, healthier lives. These technologies might help aging societies mitigate worker shortages and automate difficult and monotonous tasks. Indeed, some countries far along in the demographic transition like Japan increasingly view robots as key for augmenting a declining working-age population and meeting demand for services from a growing elderly population. With as many as 14 out of 36 OECD countries facing declining populations by 2060 (OECD 2025), Japan's long-term care (LTC) system provides a unique setting to test predictions about how robotic technologies may impact health policy and service sector labor markets in aging societies.

The broad interest in care robots is reflected in the more than 5-fold increase in publications on robots for health services between 2011 to 2021 (Trainum et al. 2024) and the growing number of studies – especially from Europe, the US and Australia – exploring assistive technologies for psychosocial support (Budak et al. 2023) or co-design for physical and mobility support (Antony et al. 2023). However, fewer studies have documented technology consistently reducing the workload of support staff (Trainum et al. 2024), despite much tantalizing suggestive evidence that such technologies could meaningfully alleviate the physical and time-crunch burdens on nurses, nurse aids and careworkers.

How will adoption of robots affect health systems and the caregiving professions, especially long-term care in aging economies? Our study explores this question by examining early diffusion of robots across hundreds of nursing homes in Japan in 2017 using nationally representative survey data. We place these results in the context of the recent surge in media attention and public interest in AI and care robotics, driven by rapid advances that have brought these technologies closer to the reliable, affordable versions that would warrant widespread adoption for long-term care in countries beyond Japan. Previous studies both in Japan and in other OECD economies have mostly focused on interviews and site observations (e.g. Kolstad et al. 2020), scoping reviews, and summary of mean adoption rates from survey data (e.g. Tosaka et al 2026). Given that robot deployment has been exploratory and sporatic across most care settings outside Japan, it is not surprising that researchers find the potential to reduce workload has not yet been realized despite “consensus among nursing staff that care robots should serve as nursing assistants to reduce workload” (Trainum et al. 2024, p.1).

Few studies empirically examine how robot adoption across hundreds of facilities is related to changes in the workflow, staff retention, or overall staffing of nursing homes and other care facilities, as our study does. Healthcare services rely heavily on the young and middle-aged workers increasingly scarce in aging economies, and face limited opportunities for automation or offshoring. Japan's case can shed light on the debate surrounding new automation technologies and their impact on workers providing services to an aging population. Although care robots are now relatively common in Japan, the early diffusion is especially relevant for many other countries, given few other countries have widely adopted care robots in long-term care. Our study contributes a set of analyses that future empirical work can build upon to document adoption patterns over time and probe causal impacts on residents and facilities such as staffing and quality of care.

Related Literature

Our paper contributes in several ways to the growing literature on robots, long-term care, and broader labor markets. Most studies of the impact of systematic robot adoption in middle- and high-income economies focus on manufacturing (e.g., Bessen, Goos, Salomons, and Van den Berge 2019; Acemoglu and Restrepo 2020; Adachi, Kawaguchi, and Saito 2020; Dauth, Findeisen, Suedekum, and Woessner 2021; Dixon, Hong, and Wu 2021). Studied settings include the US (Acemoglu and Restrepo 2020), Canada (Dixon et al. 2021), China (Cheng, Jia, Li, and Li 2019), Japan (Adachi et al. 2020), South Korea (Lee and Lee 2020), France (Acemoglu, Lelarge, and Restrepo 2020), Spain (Koch, Manuylov, and Smolka 2021), Denmark (Humlum 2019), and Germany (Dauth et al. 2021). While several studies of economy-wide robot adoption have included services (e.g. Acemoglu and Restrepo 2020; Dauth et al. 2021; Genz et al. 2021), very few focus on the service sector, and estimates for specific services like education or healthcare are often neither precise nor robust (Acemoglu and Restrepo 2020). This is an important omission because robots may play substantially different roles in the service sector (with its high concentration of tasks in which labor has a comparative advantage or automation is infeasible), especially in tight labor markets.

More recent work has begun to extend this literature into service-sector settings. Previously published studies utilized nursing home panel data to analyze how the share of care worker versus robot effort in tasks has shaped facility quality and employment (Lee et al. 2025). Beyond robotics, emerging work on artificial intelligence, including large language models, ambient AI systems embedded in care environments, and sensor-based monitoring technologies, highlights how advances in perception, communication, and real-time decision support are expanding the scope of automation in service settings (e.g., Lukac et al. 2025; Afshar et al. 2025). These technologies increasingly enable continuous monitoring, workflow coordination among nursing and care teams, and augmentation of care delivery rather than discrete task substitution, further reinforcing the importance of investigating human-machine complementarity in labor-intensive sectors such as long-term care.

Second, while previous studies have used industry-level aggregate data, we use establishment-level data from a single industry. This alleviates some of the concerns that arise from unobserved industry-level shocks that may bias the estimated effect of robot adoption, similar to other ongoing research that uses establishment- or firm-level data from the manufacturing sector (Cheng et al. 2019; Humlum 2019; Acemoglu et al. 2020; Lee and Lee 2020; Dixon et al. 2021; Koch et al. 2021). Industry-level studies that examine the impact of robots on manufacturing workers have found mixed effects, consistent with task-based theories that predict differing displacement versus reinstatement effects (e.g., Acemoglu and Restrepo 2019ab).[1] Firm-level studies generally find that robot adopters have higher total output and employment but lower labor share and production worker employment. However, identification challenges still remain in most of these firm-level studies, and virtually all are confined to the manufacturing sector (Humlum 2019; Acemoglu et al. 2020; Koch et al. 2021). Our study contributes establishment-level evidence from early diffusion of robotics in the important LTC sector utilizing a similar facility-level framework as recent studies of nursing homes (Lee et al. 2025; Tosaka et al. 2026), but capturing an earlier phase of adoption prior to the broader integration of robotics and advanced technologies.

[1] Acemoglu and Restrepo (2020) find that robot adoption has a robust negative impact on employment and wages in the US. However, Chung and Lee (2020) using the same empirical framework find that the impact of robots on local employment in the US evolves over time and eventually becomes positive in more recent years.

Third, we study service robots in an aging society, where tight labor markets are driven by long-term demographic trends increasing the scarcity of young and middle-aged labor. Japan's world-leading aging provides an ideal setting to study demography-induced endogenous development and adoption of robots for tasks performed by middle-aged workers (Acemoglu and Restrepo 2022). Our results are most relevant for regulated healthcare markets around the world and other settings where prices are regulated in the output market but not for inputs (such as wages). By studying Japan's nonprofit nursing homes, we also enlarge the scope of organizational forms studied in the literature on automation of nonproduction tasks; this is important given the prevalence of nonprofits in supplying publicly-financed services like healthcare and elderly care. Thus, in these three ways our establishment-level evidence sheds light on how service robots (as opposed to industrial robots) influence service sector organizations within aging societies.

What distinguishes our setting is not only the sector but also the technological stage. Since the late 2010s, robotics has expanded beyond simple mobility and monitoring tasks to encompass integrated care technologies, including AI-enabled safety monitoring, cognitive support for patients with dementia, and systems that optimize care workflows at the organizational level amidst the advent of generative AI (MHLW 2025; Nan et al. 2025). For example, Japan's "Society 5.0" vision aims to integrate "cyberspace and physical space" to tackle economic and societal issues (Cabinet Office, Government of Japan, 2015). Against this backdrop, the 2017 baseline is particularly valuable because it captures the stage in which robots function primarily as task-specific inputs, prior to integration into broader socio-technical systems. In contrast, contemporary adoption occurs within a more complex environment shaped by additional confounding factors, including the evolving social perception of AI, the increasing role of physician and care worker labor in training and maintaining AI systems, and the long-term implications of algorithmic bias, all of which complicate attribution of observed labor outcomes to robotics alone (Kogetsu et al. 2026).

We also speak more directly to research on nursing home markets, such as Hackmann (2019), and to work on the labor economics of long-term care provision, such as Gandhi and Grabowski (2021). Within health economics, prior studies have examined how nursing home staffing patterns relate to facility-level characteristics (Banaszak-Holl et al. 2018) and care quality (Zhang and Grabowski 2004; Castle 2008; Grabowski et al. 2013; Lin 2014; Foster and

Lee 2015; Hackmann 2019). This work also connects to the related literature on skilled nursing facilities (Rahman, Norton, and Grabowski 2016). We contribute to this literature by providing empirical evidence on several hypotheses about robot adoption and employment that flow from a task-based model of the service sector of an aging society, as set forth in related conceptual frameworks (Autor and Acemoglu 2011; Acemoglu and Restrepo 2019ab and 2022). We hypothesize that services resemble industries that rely heavily on middle-aged workers and face relatively low technological opportunities for automation. These characteristics imply that automation in services will lag that in manufacturing, but progress more quickly in aging societies relative to their younger counterparts. We hypothesize that tasks involving physical strain (such as lifting frail elderly from beds to wheelchairs) will be among the first automated, and the employees most impacted will be care workers and nurses, known as "direct-care staff," who perform daily tasks requiring physical strength, stamina, and dexterity. Such service tasks are virtually non-offshorable to countries with younger demographics, since care must take place within the local communities being served. In addition, we predict that larger nursing homes will be more likely to adopt robots, both because size correlates with success in competing for residents and expanding local market share, and because of the economies of scale in LTC robot use (e.g., monitoring robots designed to cover multiple beds per room). Finally, impacts on establishment-level employment are ambiguous, depending on the balance of the productivity-enhancing versus task-replacing impacts of robot adoption at heterogeneous establishments.

Institutional Setting

Japan's Demographic Challenges and Shortage of Care Workers

Japan's long-term care system is under growing pressure from the combined effects of low fertility, increasing longevity, and rapid population aging. As of 2024, people aged 65 and older account for 29.3 percent of the total population, while the working-age population continues to shrink (Statistics Bureau of Japan 2025). Because advanced age is strongly associated with needing assistance for daily activities, this demographic transition has contributed to a persistent shortage of care workers. Official projections more than a decade ago warned of a shortage of roughly 380,000 care workers by 2025, and more recent estimates suggest that the gap will continue widening to 570,000 workers by 2040 (Ministry of Health, Labor and Welfare (MHLW) 2017, MHLW 2025). The care labor market has therefore become increasingly tight, with the ratio of job offers to applicants about twice the average in Japan (see Appendix). The shortage is often attributed to low wages, physically demanding work, and difficult working conditions that can contribute to lower back pain.[2] The average hourly pay for care workers was 965 Yen in 2017, compared to the average minimum wage of 902 Yen.[3] In response, Japan has expanded pathways for foreign care workers and nurses through programs such as the Specified Skilled Worker (SSW) visa introduced in 2019, alongside earlier Economic Partnership Agreement (EPA) channels with countries such as Vietnam, Indonesia, and the Philippines. However, retention remains a significant challenge among both immigrant and domestic staff, given heavy workloads for care workers and nurses. For example, among migrant nurses who passed the Japanese national nursing examination between 2008 and 2019, a substantial share subsequently left Japan because of issues such as language requirements, differences in workplace culture, and demanding working conditions (Shoki et al. 2023).

Subsidizing Care Robots

Japan has long been a leader in robot production and utilization, and the government has implemented several programs to promote robots in care for older adults. On the supply side, the government has subsidized development of nursing care (or "*kaigo")* robots. In 2015, Japan's "Robot Strategy," laid out by a body within the cabinet of the Japanese government, articulated several specific goals, including increasing the share of people who want to use robots for providing care from 60% to 80%; and lowering the risk to care workers of suffering back pain by using robots for helping with transfers.[4] To achieve such goals, starting in April 2013, the Ministry of Health, Labor and Welfare (MHLW) and Ministry of Economy, Trade, and Industry (METI) identified specific task areas such as transfer aid and communication for which they subsidize development of LTC robots.

On the demand side, starting in 2015, the central government set aside funds for each prefectural government to utilize to improve LTC services. Subsidies for purchasing nursing care

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[2] A survey by the Ministry of Health, Labor and Welfare showed that 14.3% of those who left their jobs as care workers cited lower back pain as the reason.

[3] 100 Japanese Yen is approximately 1 USD.

[4] See the complete report at http://www.meti.go.jp/english/press/2015/pdf/0123_01b.pdf (METI 2015).

robots were part of a menu of items for which funds could be used. Some prefecture-level governments started subsidizing the cost of adopting LTC robots in 2015. The subsidies typically cover 50% of the cost, up to 100,000 yen (approximately US$1,000) per robot in 2017. Prefecture governments usually specify the number of robots they plan to subsidize each year, with subsidies provided on a first-come, first-served basis to nursing homes that apply. Other conditions may also apply, such as a ceiling on the number of robots for which a single nursing home may receive subsidies. We use this cross-prefectural variation in the planned number of robots subsidized as an instrument for robot adoption. Importantly, we show that pre-subsidy characteristics of prefectures are similar in prefectures with and without robot subsidies by 2017. Moreover, the administrative process leading to each prefecture's planned number of subsidized robots supports the plausible exogeneity of this instrument.[5]

Robots in Nursing Homes

The robot categories we discuss are based on the categorization of nursing care robots developed by the Japanese government and used in their survey of LTC facilities. The MHLW defines a nursing care robot (or "*kaigo* robot") as a form of robot technology that either directly aids care workers or helps the frail resident become more independent. Furthermore, the METI stipulates that a robot has three characteristics: the ability to sense information, make decisions based on that information, and take physical actions in response. Thus, we are able to distinguish robots from other kinds of technology used in care services, and can be fairly confident that the prefectural reports about nursing care robot subsidies consistently capture the same set of robotic technologies. According to the 2017 Report on Robotics in Elderly Care by the MHLW, the 10 types are robots as wearable transfer aids; nonwearable transfer aids; mobility aids; toileting aids; monitoring systems; communication support; dementia therapy; rehabilitation support; medication support; and other robots. In our analyses, we group the robots into three main categories: transfer aid robots, mobility robots, and monitoring/communication robots (Lee et al. 2025; see Appendix for more discussion).

[5] Prefecture governments aggregate municipal government plans, which are then reviewed at the national level; the central government provides each prefecture a lump sum budget, of which robot subsidies only constitute one small part; see Appendix for more details. When allocating subsidies to nursing homes within a given jurisdiction, municipalities usually do not consider the size, case mix, or whether the nursing home owns other forms of assistive technologies.

Long-term Care in Japan

In 2000, Japan implemented the Long-Term Care Insurance (LTCI) system, which provides eligible citizens above age 40 universal long-term care coverage that complements Japan's universal health coverage under social insurance. Under the LTCI system, beneficiaries are assessed by the local government according to their levels of care required or "*Kaigo* Neediness Index." The scale ranges from level 1 ("mostly able to eat and use the bathroom independently") to the most severe level 5 ("unable to use the bathroom and eat" independently and "exhibits many instances of problematic behavior or decline in understanding"). As in many high-income countries, Japan's government regulates prices for publicly covered long-term care services. These prices are standardized across nursing homes, meaning that facilities cannot compete by charging different rates. Instead, facilities compete for residents through other factors such as location, convenience, and perceived quality of care. Nursing home managers make decisions about staffing composition within government-mandated staffing ratios.

LTCI also introduced changes in the ecosystem of service delivery. For most of Japan's postwar period, long-term care was provided by local municipalities or private, non-profit corporations. This system continued with the implementation of LTCI; although some services could be procured from any private organization following the regulations set by the government, core LTCI services remained primarily with nonprofits (Suda and Guo, 2009) and a few government facilities. All facilities in the categories that we study—supplying core LTCI services in a residential setting—are not-for-profit organizations by statutory requirement.

Japan's nursing home sector includes two main types of facilities. The first is the "*tokuyo*" or special nursing homes, which provides long-term custodial care for adults who require ongoing assistance with activities of daily living such as eating, toileting, and showering. Since the allowed length of stay is unlimited, *tokuyo* are the most popular option and its residents typically remain there for the rest of their lives. The other is the "*roken*" or geriatric health services facilities, providing medium-term (3-6 month) rehabilitation services. Many *roken* residents enter after hospital discharge, making these facilities somewhat comparable to skilled nursing facilities in the United States. Across Japan, there are approximately 2.2 custodial nursing homes and 1.2 skilled nursing facilities per 100,000 people aged 65 and older, although this varies by prefecture. Demand for both types of facilities is high, with average occupancy rates of about 97 percent for custodial care homes and 90 percent for skilled nursing facilities.

Direct care in these facilities is provided by two types of workers: care workers and nurses. Care workers assist residents with activities of daily living and may hold one of several license levels, but the occupation is generally lower-paid compared with nursing. Nurses have more extensive licensing requirements and are authorized to perform clinical, rehabilitative, and caregiving tasks in medical settings such as hospitals and clinics. Japanese regulations require nursing homes to maintain at least one direct care staff member, either a care worker or nurse, for every three residents. Custodial nursing homes are only required to have a part-time physician, while skilled nursing facilities must meet an additional nurse staffing ratio of one nurse per seven residents and employ a full-time physician on staff.

Data and Empirical Strategy

Facility-Level Data

We analyze facility-level data from the annual Fact-Finding Survey on LTC Work ("*Kaigo Roudo Jittai Chousa*") collected by the Care Work Foundation in Japan. A changing cross-section of more than 8,000 LTC facilities are surveyed each year, with survey questions about adoption of robots included since 2016. The survey is fielded to a random sample of facilities that provide a variety of in-home, day-care, and residential LTC services, with a response rate of about 50%. Facilities cannot be linked across years to form a panel. In this study, we focus on approximately 860 nursing homes that responded to the survey in 2017.

To provide suggestive evidence about the representativeness of the survey, we compare to the universe of such facilities for the type most likely to adopt robots. As shown in the multiple panels of Appendix Figure 3, the distribution of size and staffing among the survey respondents is similar to those for the universe of such facilities, except that the sample facilities are slightly larger. There are no statistically significant differences between our sample and the universe of nursing homes for several key variables, including the number of residents with the most severe needs (see Appendix discussion). The survey also includes questions about human resource management.[6] We include these variables to capture differences in management practices.

The survey also includes a sample of worker-level variables. This individual-level data includes basic demographics (gender, age), work type (regular or nonregular), qualifications, tenure, full time vs. part time, and payment type (hourly vs. monthly), but not hours worked. Therefore we are unable to estimate staffing at the level of staff hours per resident day.

Prefecture-Level Data on Robot Subsidies and Labor Market Conditions

A second source of data is our compilation of prefecture-level subsidy availability and generosity. As mentioned earlier, Japan's central government and some local governments in Japan started in 2015 to provide subsidies to nursing homes to purchase LTC robots. Based on the documents we gathered, it seems clear that since 2015 more and more prefectures began to subsidize nursing homes' acquisition prices for LTC robots, typically with a maximum amount per robot. Our primary source of data was an official website that lists prefecture reports on how they utilize the funds distributed by the central government to improve LTC services in each prefecture. Prefectures use the funds to subsidize nursing homes to purchase nursing care robots. We reviewed each prefecture's annual reports starting in FY2015 to extract information on how they subsidize LTC robot purchases (see Appendix for details). We then directly contacted each prefecture and confirmed these numbers or requested them if they were missing.

From this unique dataset, we utilize two primary measures: the 2017 planned number of LTC robots in each prefecture (which comes directly from government reports); and the ratio of this planned or targeted number of robots to the number of nursing homes (both custodial and skilled nursing) in the prefecture. The latter "planned number of robots subsidized per nursing home" (or "planned robot exposure") serves as our main instrumental variable for robot adoption at the facility level. Figure 1 illustrates its magnitude and geographic variation.

We also gathered from government statistical agencies various measures of geographical variation in demography and labor markets. We use this prefecture-level data to control for prefecture characteristics that might be correlated with the decision to subsidize nursing care

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[6] These include questions about employment regulations, having a human resources manager, and retention efforts; see Appendix.

robots and labor market outcomes. These variables include total population; elderly population aged 70 and older; per capita income; minimum wage; unemployment rate; the ratio of job openings to applicants; and nursing home statistics (number of facilities, number of residents, total staffing, and capacity, by custodial vs. skilled nursing home). Consistent with the theory of forward-looking technology adoption, we control for future demand for nursing care by including estimated total population and elderly population aged 70 and older in 2040.[7]

Description of Robot Adoption Landscape

We first describe what types of robots were initially adopted for what kinds of services. In 2016, 17.6% of Japanese nursing homes reported using any type of robot, rising to 26% among the 857 nursing homes in our 2017 analytic sample. Table 1 shows that monitoring robots are the most common type of robot used by nursing homes (representing 14.9% of nursing homes); they help monitor whether individuals have gotten out of bed, fallen, or need assistance. Other common types are transfer aid robots (7.7%) to assist care workers with moving individuals such as from bed to wheelchair (4.7% wearable by the care worker, 3.3% non-wearable); mobility robots (5.3%) to assist residents with movement, toileting and bathing; and communication robots (2.8%) to provide comfort and interaction with residents.

Table 1 also shows our data on subsidies. "Robot subsidy" is an indicator variable equal to 1 if the prefecture where the nursing home is located offers a subsidy for adopting nursing care robot(s), which by 2017 covered almost three-quarters (71.9%) of the nursing homes in our sample. The planned number of robots subsidized per nursing home in a prefecture ranges from 0 to 1.162, with a mean of 0.21. Figure 2 shows a bin scatterplot with 30 bins showing the positive correlation between our instrument – planned number of robots subsidized per nursing home – and actual robot adoption by nursing homes in 2017, providing some support for our instrumental variable.

Table 2 shows other characteristics of the 857 Japanese nursing homes analyzed, with facilities dichotomized into adopters and non-adopters (of any robot). Facilities that had acquired at least one robot were slightly larger with more staff. The average nursing home in our sample (not shown) employs 42 care workers, 8 nurses, and 80 total staff, the majority (66%) of whom

[7] Acemoglu and Restrepo (2022) similarly control for projected demographic change to 2025 in their analysis of robot adoption in the 2010s.

are regular (generally full-time, monthly wage) employees. Facilities have been in operation on average for a little over 17 years, i.e., most entered the market when LTCI was launched in 2000. The wages of workers are similar among adopters and non-adopters, and the turnover rate is relatively high among all the nursing homes. About one-third report that retention of staff is a problem. Most are custodial LTC homes; skilled nursing facilities represent 20.3% of the sample. All of these nursing homes covered by public LTC insurance are not-for-profit organizations.[8]

Robot-adopting homes have slightly higher percentages of residents with lower functional status and higher care-required levels (i.e., 64% vs. 62% of residents at levels 4 and 5), representing a slightly more severe case mix than their non-adopting counterparts. Robot-adopting homes are more likely to own other forms of assistive technologies (e.g., adjustable beds), and more likely to have a human resource manager.[9] Residents per care worker plus nurse in the sampled nursing homes fall well within the required staffing ratios: custodial nursing homes average 1.2 residents per care worker plus nurse; skilled nursing homes average 1.5 residents per care worker plus nurse. Thus, the regulated ratio of residents per direct care staff is not binding on average.

Empirical Methods

We first assess the correlates of robot adoption with the following specification:

$$Robots_{jk} = \alpha_0 + \alpha_1 Z_j + \alpha_2 P_k + \alpha_3 S_k + \mu_{jk}, (1)$$

where $Robots_{jk}$ is an indicator variable for whether nursing home *j* in prefecture *k* has adopted any LTC robot. Z_j is a vector of facility *j*'s characteristics, including whether it is a custodial or skilled nursing facility; number of residents and case mix (i.e., number of residents at different care need levels); dummy variables for each technology used in the nursing home and each of the measured management practices. We also control for years of operation; location (metropolis, urban, rural); and corporation type (social welfare council, social welfare organization, medical

[8] The majority are owned and managed by social welfare organizations (78%), with 15% by medical corporations, 2.9% by local governments, and very few by other non-profit organizations like social welfare councils. Our regressions control for facility type, since as shown in Appendix Table 1, skilled nursing facilities differ from custodial nursing homes in several important respects: they are slightly less likely to adopt robots (23% vs 26% for custodial homes), with the largest difference for monitoring and communication robots. Skilled nursing homes also are larger than the average custodial home (89 vs 62 residents), with more nurses per resident and fewer care workers per resident.

[9] See Appendix Figures for the prefectural variation in the unemployment rate and in robot adoption.

corporation, local government, and other). Also included in Z_j are facility manager perceptions regarding shortage of care workers and nurses, and difficulty of hiring care workers. We created these variables by averaging across nursing homes in the same locality,[10] but excluding nursing home *j* (we label these leave-one-out variables as "labor shortage perception controls" in the tables). These variables are helpful because they can further control for within-prefecture local labor market conditions.

P_k is a vector of prefecture characteristics, including per capita income, unemployment rate, total population, population aged 70 or older, minimum wage, number of nursing homes, occupancy rate of nursing homes, and job applicants per opening, number of people certified for different care levels, population estimates in 2040 (total and age 70 or older), and whether there were subsidies to secure workers or improve facilities. S_k is planned number of robots subsidized per nursing home in prefecture *k.* The α's are parameters to be estimated, and $\mu_{jk}$is the error term. This regression in turn becomes the first stage for our IV strategy to study the impact of robot adoption on staffing, where S_k is the excluded instrument.

To identify the effect of robot adoption on staffing, we estimate regressions of the following form:

$$Y_{jk} = \alpha_0 + \alpha_1 Robots_{jk} + \alpha_2 Z_j + \alpha_2 P_k + \mu_{jk}, (2)$$

where Y_j represents various staffing measures of nursing home *j* in prefecture *k* in 2017 (e.g., log(care workers), log(nurses), log(total number of workers)). The $Robots$ indicator variable for robot adoption is the primary variable of interest. The other control variables for facility and prefecture characteristics are as specified above. We cluster standard errors at the prefecture level.

We also examine the effect of robot adoption on revenue growth and retention of care workers. To do so, we estimate Equation (2) replacing Y_j by the percentage increase in *j*'s revenue in September 2017 over the same month in 2016. The outcome for the retention regression is a dummy variable indicating that the facility manager considers retention of workers at the nursing home to be low and problematic. Given the physically demanding nature of care giving and relatively low pay, retention can be a challenge in many nursing homes.

[10] The survey indicates whether the nursing home is in a large, medium, or small municipality within a prefecture. We take the average by these "localities."

There are potential endogeneity issues with these specifications. Nursing home adoption of robots may be correlated with other factors such as unobserved aspects of quality and management that also determine their staffing. We use an IV approach based on prefecture-level subsidies for robot adoption. One concern about the instrument is that the decision to subsidize nursing care robots may be correlated with local labor market conditions, which may also affect staffing of nursing homes. To check the importance of this issue, in the Appendix we show that labor market conditions do not differ noticeably between prefectures that subsidize nursing care robots and those that do not. These "randomization test" results indicate that the two groups of prefectures are similar in facing challenges due to population aging and care worker shortage, but differ in the timing of introducing robot subsidies, possibly for idiosyncratic reasons such as capacity, perceptions, and priorities of prefecture governments. Subsidization increases over time such that 43 out of 47 prefectures had introduced robot subsidies by 2019.

To further mitigate endogeneity concerns, we also control for various demand- and supply-side factors that would affect the tightness of the labor market, as well as facility managers' perceptions regarding the difficulty of hiring care workers. This facility-level measure of the tightness of the local labor market lessens the endogeneity concern that unobserved local market conditions are correlated with both robot adoption and hiring decisions. Additionally, to control for future demand for LTC, we include the estimated elderly population aged 70 and older in 2040 in each prefecture as well as the total population. Kleibergen-Paap rk Wald F statistics are reported for the first stage of the 2SLS regressions and we cluster the standard errors at the prefecture level.[11]

Empirical Results

Robot Adoption

[11] When we examine in a multivariate regression whether these prefecture-level demand- and supply-side factors are related to whether a prefecture subsidizes LTC robots, we find that none of the covariate estimates are statistically significant (Appendix). See Appendix Figures also for the prefectural variation in the unemployment rate and in robot adoption. We also undertook several diagnostic tests, including plotting pre-determined prefecture-level variables against the instrument, in the spirit of Pei et al. (2019). None of the coefficient estimates are significant at the 5% level.

What are the primary predictors of LTC robot adoption? Table 3 shows the results for our estimation of equation (1). In our most parsimonious specification (Table 3 column 1), we see that nursing home size, as measured by number of residents served, is a strong positive predictor of robot adoption, consistent with our hypothesis. Adding variables for case-mix of residents (column 2), we see that a higher share of the most functionally impaired residents (i.e., care-level-required 5) is positively correlated with adopting robots. This association appears to arise through association with other technologies for caregiving for the most functionally impaired, such as wheelchair lifts and wheelchair scales, which are strongly correlated with robot adoption (column 3). When we also control for management practices at the nursing home (column 4), we find that having a human resources manager and "seeking to improve wages for retention" (as reported on the survey) are strongly associated with robot adoption. Those management practices continue to be strongly associated with robot adoption when we also add prefectural characteristics (column 5), additional facility characteristics (column 6), and constructed variables related to perceptions of labor shortage in the locality (column 7).[12] Finally, we see in the last three columns of Table 3 that the planned number of robots per nursing home in 2017 (the first row) is a strong and significant predictor of robot adoption, whether controlling for overall size (column 8) or for residents' case mix as well as number (column 9), and when estimating with a logit model (column 10). Planned number of robots per nursing home is our instrument for identifying causal effects of robot adoption on staffing. We use the column 9 specification for our IV regression.

Results on Robot Adoption and Staffing

Table 4 columns 1-3 show results for OLS regressions of staffing on robot adoption among the 857 nursing homes. Panel A focuses on all employees (both regular and non-regular employees), Panel B on regular employees, and Panel C on non-regular employees. Regular employees are those with no fixed employment period. Non-regular employees are other employees including contract and part-time employees. Non-regular employees are on more flexible work contracts with fewer benefits, and often work part-time. The three columns show the different kinds of staff: care workers, nurses, and total number of workers (whether providing

[12] The Appendix presents the coefficient estimates on the additional variables included in columns 5 to 7.

care or other managerial and logistic support). Robot adoption is positively correlated with nurse staffing, though not statistically significantly so for non-regular nurses (column 2). Robot-adopting nursing homes have between 3 to 8 percent more staff than their non-adopting counterparts.

Table 4 columns 4-6 report our staffing results using planned number of robots subsidized per nursing home in 2017 as the IV. The estimated coefficient of robot adoption is positive and significant for both care workers and nurses in the staffing regressions (Table 4 columns 4 and 5). The estimate magnitude suggests that robot adoption is associated with 28% more care workers and 39% more nurses. Total employment is about 26% higher (Column 6). However, the increases in staffing occur entirely among the non-regular employees. Robot adoption approximately doubles the number of non-regular care workers (from an average of about 12 employees) and increases the number of non-regular nurses by about 78% (from an average of about 2.5 employees). The estimates on regular employees are negative but not significant. These findings indicate that robot adoption may not displace workers but rather increase care workers and nurses with more flexible labor contracts, and may complement other investments in quality of care. These results are consistent with the anecdotal evidence (discussed in the Related Literature section and the Appendix) that robots reduce the burden of care and may enhance quality of care.[13]

After using the instrumental variable, the coefficient estimates on robot adoption become significantly positive (Table 4 columns 1-3 compared to columns 4-6). This may happen, for example, if an unobserved negative shock in the staffing regression (such as the difficulty of hiring caregivers in the local market, which negatively affects the number of workers) is correlated with robot adoption by the nursing home. Such a correlation seems plausible and would negatively bias the OLS estimate for robot adoption; the IV regression that removes the confounding effect would therefore result in a more positive coefficient estimate.

[13] We also conducted our own survey in January 2020 asking more than 700 nursing-home facility managers whether robots help care workers. Respondents overwhelmingly agreed that 'wearable transfer robots reduce workers 'physical burden such as pain '(85.7% agreed or strongly agreed); 'non-wearable transfer robots reduce worker physical burden '(87.6%); 'monitoring robots relieve worker mental stress '(72.1%); and 'monitoring robots help workers understand and monitor residents 'behaviors '(77.1%).

We also find that revenue growth is not significantly impacted by robot adoption (Table 5). This may be because public nursing homes generally operate at near full capacity and have little room to increase the number of residents in the short-term.

Table 6 column 1 examines whether robot adoption affects retention of workers. The estimation result indicates that robot adoption reduces the likelihood that the nursing home considers retention problematic, which suggests that robots may indeed help reduce the burden on care workers and nurses. This is consistent with our finding that robot adoption is negatively associated with turnover of care workers, though it is not statistically significant (see Appendix).

Immigration is an important issue for many countries' long-term care systems. Health economists have studied the impact of immigrant nurses and other direct care staff (e.g., Cortés and Pan 2014, Grabowski et al. 2023). For Japan, the use of immigrant employees is especially of interest, as policies that originally discouraged immigration have gradually been relaxed, in part to relieve the shortfall of LTC workers. In Table 6 columns 2 and 3, we show OLS and 2SLS results regarding nursing home hiring of immigrant workers in 2017. Nursing homes that adopt robots (especially aid robots) are more likely to have hired immigrant workers, but this association does not appear to be causal (Panel B). Plans to hire immigrant labor show a similar pattern: while future hiring of immigrant workers has a significant positive association with robot adoption, the 2SLS estimate is indistinguishable from zero.

In the Appendix, we examine the robustness of our IV results on staffing using a different instrumental variable: the planned number of robots subsidized per nursing home in 2016. The first-stage F-statistics are somewhat smaller, though still considerably greater than 10. Overall, we find qualitatively and quantitatively results. We also find that results are not sensitive to the inclusion of skilled nursing facilities or when controlling for the number of different types of services provided by the nursing home.

Discussion

The same new wave of technologies that inspires fear or hesitation in many countries is often viewed in Japan as a remedy for the social and economic challenges posed by Japan's demography: a declining overall population and increasing proportion of elderly, while eschewing large-scale immigration. Japan has been actively developing and subsidizing deployment of robots in nursing homes to deal with labor shortages and high turnover rates among LTC workers.

Our empirical analysis of nationally representative data from Japanese nursing homes finds that transfer aids and monitoring robots are the most common types adopted, and there is a positive relationship between robot adoption and the number of direct care staff, primarily non-regular workers. Employment contracts for these non-regular workers often are temporary and flexible, offering fewer benefits than those enjoyed by regular employees and often part-time. Thus the impact on full-time-equivalent staffing may be neutral, if homes are substituting from hiring full-time workers to more than one part-time worker. Our evidence suggests that the employment implications of robot adoption are concentrated among non-regular workers. Adoption of monitoring robots might have promoted part-time work, a form of work contract that the Japan Nursing Association has encouraged to reduce stress on nurses and promote work-life balance. Whether overall staffing per resident day increases or declines remains an open question (since we lack data on care hours). Future research with hours worked could help to clarify these effects in different settings.

Moreover, consistent with reduced burden of care, robot adoption appears to reduce the likelihood of nursing homes reporting difficulty in staff retention. This suggests that quality may be improved, or at least not damaged. Indeed, our finding that robots are associated with higher nurse staffing per resident, controlling for resident case mix, hints that robot adoption may bring positive impacts on quality.

Taken together, our findings provide evidence that robot adoption may not reduce jobs, but may promote more flexible work, either by increasing the tasks performed by non-regular employees or potentially encouraging part-time work. These findings are consistent with more recent survey-based evidence from 2020-22 (Lee et al. 2025; Tosaka et al. 2026). According to a government survey on the effectiveness of care robots,[14] 42% of workers who have used monitoring robots find that they reduce psychological burden, and 32% say they reduce the number of visits to residents' rooms. Obayashi and Masuyama (2020) also find that communication robots help reduce the burden on care workers during night shifts.

[14] Research project on the effectiveness of nursing care robots https://www.mhlw.go.jp/content/12601000/000488463.pdf (in Japanese) (accessed November 23, 2020).

Overall, this empirical evidence from Japan suggests that robot adoption can augment the care workforce and improve retention, potentially improve continuity and quality of care while mitigating careworker shortages.

Our study contributes to the literature on automation within aging societies by leveraging unique establishment-level data, complementing a few previous studies that use firm-level data to open the “black box” of organizational adaptation, including how robots displace or augment specific labor tasks. Most such studies find that larger firms adopt robots (Acemoglu et al. 2020; Bonfiglioli et al. 2020, Koch et al. 2021). Thus, our finding of higher employment in robot-adopting establishments is consistent with previous empirical work in both the industrial and service sectors (e.g., Dauth et al. 2019), underscoring that these trends apply to a wider range of sectors and organizational forms than previously documented. Firm- or facility-level evidence on the labor market impact of robotics in the service sector is limited and valuable, because most middle- and high-income economies have large service sectors; accordingly, establishment-level evidence about robot use in service delivery, as in the present study, may be even more important than industrial robot diffusion for understanding future economic impacts of “physical AI” and robotics in these economies, including their growing health sectors.

Our findings complement recent work examining care robot adoption in Japan and other economies. While our study focuses on the labor market consequences of adoption in the early stage that is similar to the contemporary US, South Korea, or China, Lee at al. (2025) and Tosaka et al. (2026) study the correlates and implications of robot adoption using more recent Japanese data when robots are relatively commonplace. Tosaka et al. (2026) found that adoption is strongly associated with facility size, other equipment use, younger workforces, and the presence of employment management supervisors. These results suggest that robot adoption increasingly occurs within facilities that possess greater technological and managerial capacity. These findings together suggest that the benefits of robot adoption in reducing care worker burden may persist as adoption expands, even as the underlying mechanisms evolve from task-specific assistance toward more integrated forms of support.

In the most closely-related empirical work (by an overlapping group of coauthors as the present study), Lee et al. (2025) collect survey data on robot deployment in Japanese nursing homes between 2020 and 2022. They find that residents in homes that use robots have fewer pressure ulcers and are restrained less often. By these metrics, robots are associated with improved quality of care (controlling for facility size, management practices, locality, and so on). Lee et al. (2025) also find an increasing share of specific care tasks performed by robots. This pattern underscores the importance of collecting such data early in the adoption process to understand how tasks shift over time, and how such robots or "cobots" might change worker tasks as technology augments their work rather than replaces them.

While the Lee et al. (2025) survey data is from a sample of responding nursing homes, the evidence we present in this study is nationally representative for Japan. Moreover, the Lee et al. (2025) study results are correlational, not necessarily causal, based on panel data controlling for the characteristics of facilities and their localities (including COVID). The present study employs an IV strategy to suggest causal effects, although further probing of the causal impact of robots on care outcomes in different settings is warranted.

The consistent patterns between different periods of adoption and samples of nursing homes in Japan suggest that "physical AI" may hold considerable potential for the future of caregiving in aging societies. At least for countries already far along the demographic transition and with limited domestic care workforces, care robots have the potential to enhance quality of care while augmenting careworkers so they can focus more on "human touch" care and less on the backpain-inducing physical tasks that make care work such a high-turnover job.

These potential benefits, however, depend on how robots are adopted and integrated into direct-care workflows. Prior studies find that robots can reduce some forms of physical burden and improve emotional wellbeing among older adults, including suggestive evidence about improved mood and emotional wellbeing, increased social interaction, reduced loneliness, cognitive stimulation, and in some cases reduced pain and medication use (Trainum et al. 2023). In the physical domain, feeding assistive robots have enabled patients to eat more independently, reducing the hands-on demands placed on caregivers; lifting robots have alleviated physical burden and reduced musculoskeletal strain; automated bathing systems have complemented or replaced caregiver involvement in personal hygiene; and monitoring robots have automatically recorded vital information (Persson et al. 2021).

However, integrating robots into care processes can also result in new work in the form of technical problems and biases, maintenance labor, and the need for staff to mediate resident-robot interactions (Persson et al. 2021; Trainum et al. 2023). This makes the distinction between augmentation and replacement especially important: nursing staff tend to be more receptive to robots that support indirect or physically demanding tasks, while raising stronger concerns about robots taking over intimate or relational forms of care such as bathing, feeding, companionship, and emotional support that remove human touch from the care relationship (Trainum et al. 2024). Informal caregivers surveyed in Hungary expressed strong willingness to incorporate robotic assistance, identifying movement support, help with daily tasks, and emergency call functions as the most valued capabilities, while remaining more hesitant about robots performing intimate tasks such as feeding or personal care (Vágvölgyi et al. 2025). Sustained, peer-led training also appears important, since orientation to care robots is better understood as an ongoing workplace process rather than a one-time technical introduction (Tuisku et al. 2022).

Understanding the factors that facilitate entry-level adoption of robotics in long-term care settings and their potential impacts – our goal for this study – is particularly relevant for policymakers seeking evidence about the social value of "embodied AI" in countries facing similar demographic pressures, including but not limited to Italy, China, South Korea, and Germany. In South Korea, for example, the Korea Immigration Service Foundation predicted a substantial shortage of care workers by 2028, reflecting concerns about a limited skilled labor supply and rising care demand that mirror those observed in Japan (Park 2026).

Our results are also relevant for other health services with regulated prices but freedom in wage-setting and in choice of other inputs. As the large literature on the economics of healthcare and long-term care in Europe and the US Medicare and Medicaid programs demonstrates, regulated prices do not preclude competition for market share, widespread adoption of new technologies, and labor market adjustments. Japan's experience with robotics in long-term care may provide insights relevant for many other economies with burgeoning cohorts of older adults and strained caregiving workforces.

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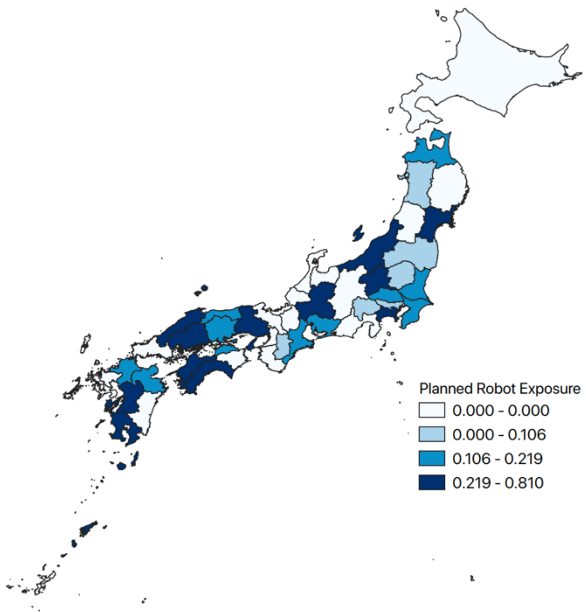
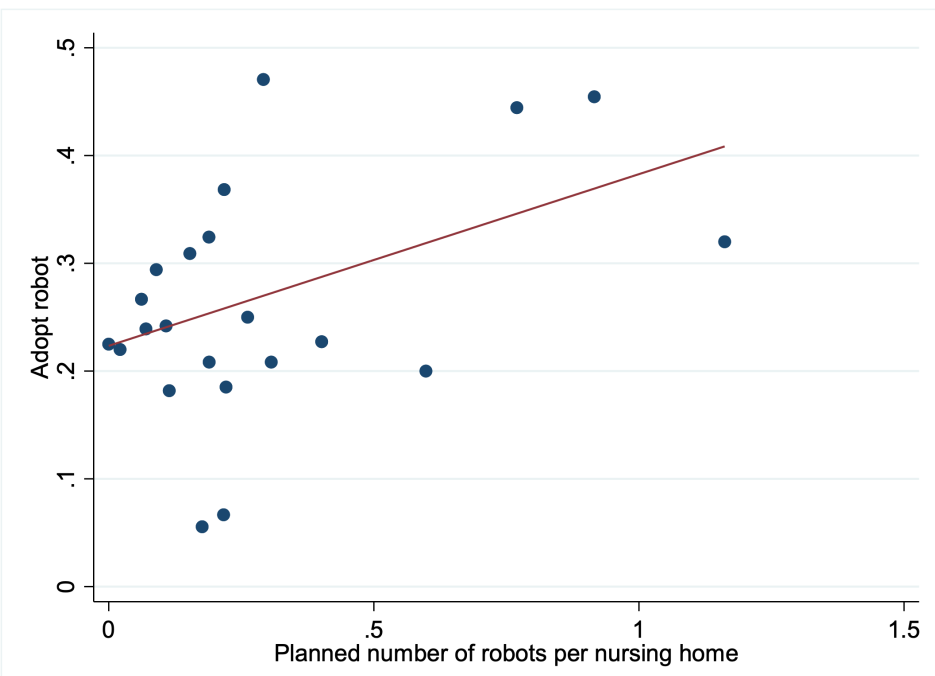
Figure 1. Subsidies to nursing homes in Japan for purchasing LTC robots: Planned robot exposure (2017)



Source: Ministry of Health, Labor and Welfare, Japan. Various years. Prefectural report on funds set aside to improve health care and LTC service in each prefecture.

Map source: GADM ver. 3.6, Center for Spatial Sciences at the University of California, Davis

Figure 2: Subsidies for nursing care robots predict robot adoption, 2017



Source: Binscatter plot, using 30 bins, based on authors' compiled dataset of nursing home subsidies and 2017 survey data on Japanese nursing homes. The horizontal axis is the prefecture's planned number of robots to have adopted, divided by the number of custodial and skilled nursing homes in that prefecture in 2017.

Table 1. Robot adoption and subsidy

	Mean	Std. Dev.	Min	Max
Adopt any robots	0.260	0.439	0	1
Adopt transfer aid robots	0.077	0.267	0	1
Transfer aid: wearable	0.047	0.211	0	1
Transfer aid: non-wearable	0.033	0.178	0	1
Adopt mobility robots	0.053	0.223	0	1
Mobility aid: outdoor	0.005	0.068	0	1
Mobility aid: indoor	0.008	0.090	0	1
Excretion support	0.005	0.068	0	1
Bathing support	0.029	0.168	0	1
Adopt monitoring or communication robots	0.174	0.379	0	1
Monitoring robots	0.149	0.357	0	1
Communication robots	0.028	0.165	0	1
Robot subsidy	0.719	0.450	0	1
Planned number of robots subsidized per nursing home	0.210	0.269	0	1.162

Note: Number of observations is 857.

Table 2. Descriptive statistics

	Robot adopter (N=223)		Robot non-adopter (N=634)		Difference of Means	
	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error
Number of care workers	47.700	1.498	40.35	0.753	7.350***	1.556
Number of nurses	8.683	0.295	7.695	0.199	0.988***	0.380
Number of total staff	87.429	2.838	77.635	2.717	9.794**	4.925
Number of care workers - regular employees	33.004	1.060	28.162	0.569	4.842***	1.153
Number of nurses - regular employees	5.604	0.243	5.11	0.163	0.494	0.312
Number of total staff - regular employees	56.754	1.814	51.928	2.037	4.826	3.634
Care worker log monthly wage	12.498	0.006	12.496	0.003	0.002	0.006
Nurse log monthly wage	12.724	0.011	12.708	0.008	0.016	0.015
Manager log monthly wage	13.272	0.027	13.23	0.02	0.041	0.038
Separation rate of care workers	0.143	0.007	0.156	0.009	-0.013	0.015
Hiring rate of care workers	0.162	0.010	0.161	0.005	0.001	0.011
Turnover rate of care workers	0.305	0.016	0.316	0.012	-0.012	0.023
Report retention as a problem	0.307	0.030	0.327	0.018	-0.020	0.035
Hire foreign workers	0.208	0.026	0.143	0.013	0.065**	0.027
Plan to hire foreign workers	0.405	0.032	0.297	0.017	0.108***	0.035
Years of operation	17.715	0.578	17.709	0.387	0.005	0.742
Number of residents requiring care level 1, 2, or 3	25.446	1.246	25.46	0.786	-0.014	1.526
Number of residents requiring care level 4	24.633	0.813	22.287	0.405	2.347***	0.839
Number of residents requiring care level 5	20.921	0.681	18.788	0.412	2.133***	0.808
Care workers per resident	0.720	0.022	0.684	0.025	0.035	0.045
Nurses per resident	0.130	0.004	0.124	0.003	0.006	0.006
Skilled nursing home	0.183	0.025	0.211	0.015	-0.027	0.030
Social welfare council	0.017	0.008	0.021	0.005	-0.005	0.011
Social welfare organization	0.842	0.024	0.784	0.016	0.058*	0.030
Medical corporation	0.121	0.021	0.15	0.014	-0.030	0.026
Local government	0.008	0.006	0.029	0.006	-0.020*	0.011

Wheel chair lifts	0.825	0.025	0.722	0.017	0.103***	0.032
Adjustable beds	0.954	0.014	0.918	0.01	0.036*	0.019
Seat lifting wheel chair	0.108	0.020	0.09	0.011	0.018	0.022
Special bathtub	0.863	0.022	0.799	0.015	0.063**	0.029
Stretcher	0.938	0.016	0.867	0.013	0.071***	0.024
Wheel chair for showers	0.742	0.028	0.649	0.018	0.093***	0.035
Wheel chair scale	0.983	0.008	0.9	0.011	0.084***	0.020
Has employment regulation for non-regular workers	0.908	0.019	0.926	0.01	-0.017	0.020
Has a HR manager	0.675	0.030	0.58	0.019	0.095***	0.036
Has a wage table	0.938	0.016	0.911	0.011	0.026	0.021
Improve working conditions for retention	0.579	0.032	0.576	0.019	0.003	0.037
Improve wages for retention	0.592	0.032	0.451	0.019	0.140***	0.037
Additional Provider Payment	0.988	0.007	0.971	0.006	0.016	0.012

Table 3. Robot adoption

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent variable: Adopt robot									
			Other tech	*+Management practices*	*+Prefecture characteristics*	*+Facility characteristics*	*+Leave-one-out variables*	*Subsidy*		*Subsidy* (logit estimates)
Planned number of robots per nursing home in 2017								0.423***	0.428***	2.655***
								(0.0892)	(0.0896)	(0.523)
Skilled nursing home	0.0323	0.0926	0.0855	0.0947	0.0791	0.0914	0.0837	0.0232	0.0690	0.597
	(0.0628)	(0.0660)	(0.0667)	(0.0677)	(0.0695)	(0.0705)	(0.0736)	(0.0659)	(0.0706)	(0.416)
Log(number of residents)	0.0983***							0.0661*		
	(0.0306)							(0.0340)		
Log(care level 1~3 residents)		-0.00246	-0.00728	-0.0101	-0.00772	-0.0111	-0.0104		-0.0105	-0.0695
		(0.0249)	(0.0247)	(0.0247)	(0.0248)	(0.0262)	(0.0264)		(0.0262)	(0.162)
Log(care level 4 residents)		0.0320	0.0191	0.0125	0.0189	0.0222	0.0245		0.0400	0.305
		(0.0359)	(0.0357)	(0.0356)	(0.0353)	(0.0361)	(0.0363)		(0.0361)	(0.254)
Log(care level 5 residents)		0.0591**	0.0510*	0.0534*	0.0456	0.0344	0.0283		0.0278	0.186
		(0.0301)	(0.0308)	(0.0305)	(0.0308)	(0.0319)	(0.0327)		(0.0324)	(0.207)
Wheel chair lifts			0.0730**	0.0694**	0.0740**	0.0863***	0.0774**	0.0805**	0.0800**	0.500**
			(0.0321)	(0.0316)	(0.0321)	(0.0333)	(0.0338)	(0.0341)	(0.0341)	(0.221)
Adjustable beds			-0.0785	-0.0840	-0.0929*	-0.122**	-0.138**	-0.147**	-0.153***	-0.830**
			(0.0573)	(0.0552)	(0.0529)	(0.0563)	(0.0566)	(0.0579)	(0.0575)	(0.370)
Seat lifting wheel chair			0.0190	-0.00234	-0.00401	0.0164	0.0176	0.0180	0.0167	0.110
			(0.0517)	(0.0515)	(0.0502)	(0.0532)	(0.0528)	(0.0519)	(0.0520)	(0.280)
Special bathtub			0.0141	0.0125	0.0209	0.00470	-0.0105	-0.0149	-0.0148	-0.0652
			(0.0390)	(0.0384)	(0.0393)	(0.0407)	(0.0426)	(0.0419)	(0.0419)	(0.259)
Stretcher			0.0557	0.0563	0.0614	0.0575	0.0770*	0.0846*	0.0809*	0.607*
			(0.0445)	(0.0438)	(0.0439)	(0.0472)	(0.0463)	(0.0464)	(0.0464)	(0.330)

Wheel chair for showers			0.0245	0.0261	0.0295	0.0282	0.0263	0.0292	0.0285	0.123
			(0.0316)	(0.0317)	(0.0319)	(0.0331)	(0.0336)	(0.0331)	(0.0331)	(0.204)
Wheel chair scale			0.165***	0.156***	0.155***	0.145***	0.158***	0.153***	0.149***	1.464***
			(0.0373)	(0.0365)	(0.0369)	(0.0383)	(0.0391)	(0.0406)	(0.0403)	(0.484)
Has employment regulation for non-regular workers				-0.0517	-0.0500	-0.0165	-0.0114	-0.0229	-0.0241	-0.125
				(0.0551)	(0.0552)	(0.0604)	(0.0618)	(0.0616)	(0.0615)	(0.359)
Has a HR manager				0.0562*	0.0633**	0.0457	0.0634**	0.0739**	0.0737**	0.463**
				(0.0294)	(0.0294)	(0.0311)	(0.0315)	(0.0312)	(0.0311)	(0.193)
Has a wage table				0.00860	0.0158	0.0265	0.0232	0.0248	0.0231	0.226
				(0.0496)	(0.0500)	(0.0537)	(0.0553)	(0.0538)	(0.0537)	(0.364)
Improve working conditions for retention				-0.0203	-0.0161	-0.0227	-0.0258	-0.0206	-0.0236	-0.141
				(0.0291)	(0.0292)	(0.0304)	(0.0309)	(0.0304)	(0.0305)	(0.185)
Improve wages for retention				0.0923***	0.0910***	0.0830***	0.0836***	0.0891***	0.0901***	0.554***
				(0.0289)	(0.0290)	(0.0303)	(0.0309)	(0.0305)	(0.0305)	(0.184)
Additional Provider Payment						-0.0253	-0.0135	-0.0253	-0.0296	-0.129
						(0.0777)	(0.0776)	(0.0788)	(0.0787)	(0.633)
Observations	938	938	938	938	938	884	857	857	857	857
R-squared	0.029	0.032	0.054	0.070	0.101	0.113	0.127	0.153	0.154	

Notes: All regressions additionally control for years of operation, location (metropolis, urban, rural), corporation type (social council, social organization, medical facility, local government facility, and other), region fixed effects (we divide Japan into 7 regions), and a dummy for skilled nursing homes. Standard errors clustered by prefecture are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4. Robot adoption and staffing

	OLS Estimates			IV Estimates		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Log(number of care workers)	Log(number of nurses)	Log(total number of employees)	Log(number of care workers)	Log(number of nurses)	Log(total number of employees)
Panel A. All employees						
Adopt robots	0.0429	0.0684**	0.0582*	0.278***	0.388***	0.255**
	(0.0324)	(0.0307)	(0.0352)	(0.0737)	(0.125)	(0.106)
Observations	857	857	857	857	857	857
R-squared	0.429	0.506	0.386			
First stage F-statistic				73.486	73.486	73.486
Panel B. Regular employees						
Adopt robots	0.0306	0.0680*	0.0470	-0.0780	-0.00082	-0.0418
	(0.0395)	(0.0361)	(0.0376)	(0.121)	(0.115)	(0.135)
Observations	857	857	857	857	857	857
R-squared	0.408	0.476	0.397			
First stage F-statistic				73.486	73.486	73.486
Panel C. Non-regular employees						
Adopt robots	0.0798	0.0414	0.0848	1.062***	0.784***	0.76***
	(0.0553)	(0.0522)	(0.0524)	(0.167)	(0.264)	(0.145)
Observations	857	857	857	857	857	857
R-squared	0.254	0.212	0.282			
First stage F-statistic				73.486	73.486	73.486
Base facility characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Resident case-mix	Yes	Yes	Yes	Yes	Yes	Yes
Other technology adoption	Yes	Yes	Yes	Yes	Yes	Yes
Management practices	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture characteristics	Yes	Yes	Yes	Yes	Yes	Yes

HR development practices	Yes	Yes	Yes	Yes	Yes	Yes
Labor shortage perceptions	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Base facility characteristics control for years of operation, location (metropolis, urban, rural), corporation type, and skilled nursing homes. Resident case-mix controls for the log number of residents with care levels 1-3, 4, and 5. Other technology adoption controls for each non-robot technology used in the nursing homes. Management practices control for human resource management practices. Prefecture characteristics controls for the demographic and economic conditions. HR development practices control for human resource development practices in a facility. Labor shortage perceptions control for labor shortage perceptions on care workers, nurses, and laborers in general. Standard errors clustered by prefecture are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5. Revenue growth

VARIABLES	(1) OLS Revenue growth (%)	(2) 2SLS Revenue growth (%)
Panel A. Adopt any robot		
Adopt robots	-1.109	-4.369
	(0.951)	(3.949)
Observations	802	802
R-squared	0.084	
First stage F-statistic		68.145
Panel B. Robot adoption by type		
Aid robots	0.105	
	(1.482)	
Mobility robots	0.877	
	(1.632)	
Monitoring and Communication robots	-1.467	
	(1.182)	
Observations	802	
R-squared	0.084	
Panel C. Robot adoption by time		
Robot first adopted before 2017	-1.177	
	(0.997)	
Robot first adopted in 2017	-1.719	
	(1.847)	
Observations	802	
R-squared	0.084	
Base facility characteristics	Yes	Yes
Resident case-mix	Yes	Yes
Other technology adoption	Yes	Yes
Management practices	Yes	Yes
Prefecture characteristics	Yes	Yes

HR development practices	Yes	Yes
Labor shortage perceptions	Yes	Yes

Notes: Worker characteristics control for gender, age, age squared, experience, experience squared, and qualification level of the worker. Base facility characteristics control for years of operation, location (metropolis, urban, rural), corporation type, region fixed effects (we divide Japan into 6 regions), and skilled nursing homes. Resident case-mix controls for the log number of residents with care levels 1-3, 4, and 5. Other technology adoption controls for each non-robot technology used in the nursing homes. Management practices control for human resource management practices. Prefecture characteristics controls for the demographic and economic conditions. HR development practices control for human resource development practices in a facility. Labor shortage perceptions control for labor shortage perceptions on care workers, nurses, and laborers in general. Standard errors clustered by prefecture are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6. Careworker Retention and Hiring Immigrant Workers

	(1) Retention is difficult	(2) Hire immigrant workers	(3) Plan to hire immigrant workers
Panel A. OLS estimates			
Adopt robots	-0.0157	0.0633**	0.0641*
	(0.0394)	(0.0321)	(0.0385)
Observations	846	852	849
R-squared	0.070	0.111	0.116
Panel B. 2SLS estimates			
Adopt robots	-0.258**	-0.0382	-0.0288
	(0.123)	(0.133)	(0.130)
Observations	846	852	849
First stage F-statistic	73.55	72.928	73.788
Base facility characteristics	Yes	Yes	Yes
Resident case-mix	Yes	Yes	Yes
Other technology adoption	Yes	Yes	Yes
Management practices	Yes	Yes	Yes
Prefecture characteristics	Yes	Yes	Yes
HR development practices	Yes	Yes	Yes
Labor shortage perceptions	Yes	Yes	Yes

Notes: Worker characteristics control for gender, age, age squared, experience, experience squared, and qualification level of the worker. Base facility characteristics control for years of operation, location (metropolis, urban, rural), corporation type, region fixed effects (we divide Japan into 6 regions), and skilled nursing homes. Resident case-mix controls for the log number of residents with care levels 1-3, 4, and 5. Other technology adoption controls for each non-robot technology used in the nursing homes. Management practices control for human resource management practices. Prefecture characteristics controls for the demographic and economic conditions. HR development practices control for human resource development practices in a facility. Labor shortage perceptions control for labor shortage perceptions on care workers, nurses, and laborers in general. Standard errors clustered by prefecture are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix A. *Kaigo* Neediness Index

Level 1

1. Requires some form of help in taking care of the surroundings (such as cleaning).
2. Requires some form of assistance for complex movements such as standing up.
3. Requires some form of support for walking and remaining in a standing position.
4. Mostly able to eat and use the bathroom independently.
5. Exhibits problematic behavior or decline in understanding.

Level 2

1. Requires some form of help for all tasks to take care of the surroundings.
2. Requires some form of assistance for complex movements such as standing up.
3. Requires some form of support for walking and remaining in a standing position.
4. Requires some form of support for eating and using the bathroom.
5. Exhibits problematic behavior or decline in understanding.

Level 3

1. Unable to take care of the surroundings on one's own.
2. Unable to do complex movements such as standing up.
3. At times unable to walk or remain in a standing position.
4. Unable to use the bathroom independently.
5. Exhibits several instances of problematic behavior and all-round decline in understanding.

Level 4

1. Hardly able to take care of one's surroundings.
2. Hardly able to do complex movements such as standing up.
3. Unable to walk or remain in a standing position on one's own.
4. Unable to use the bathroom.
5. Exhibits many instances of problematic behavior or decline in understanding.

Level 5

1. Hardly able to take care of one's surroundings.
2. Hardly able to do complex movements such as standing up.
3. Hardly able to walk or remain in a standing position.
4. Unable to use the bathroom and eat.
5. Exhibits many instances of problematic behavior or decline in understanding.

Appendix B: Conceptual framework, additional institutional context and empirical results, with supplementary figures and tables

Conceptual Framework and Related Studies

Previous studies have highlighted the importance of establishment-level data for better understanding the relationship of AI/robotics and other new technologies with labor markets and productivity (e.g., National Academies of Sciences, Engineering, and Medicine 2017; Raj and Seamans 2019; Frank et al. 2019).[1] In the setting of LTC for the elderly, demographic change may have already spurred significant development of robotics technology (Acemoglu and Restrepo 2022) and the belief that robots can substitute for tasks relying on middle-aged workers, bolstering the declining supply of care workers as the demand for care (i.e., the number of older adults requiring LTC) continues to grow. However, the caring professions have also often been held up as among the few for which robotics and AI provide poor substitutes, at least for the tasks involving physical dexterity, empathetic communication, and emotional connection (McKinsey Global Institute 2017, Jackson 2019). These areas embody the continuing or new tasks in which labor has a comparative advantage. Furthermore, as economists have pointed out going back at least to the pioneering work of Griliches (1969), capital may be complementary to specific skills of workers; such capital-skill complementarity might lead robot-adopting nursing homes to hire more nurses and fewer care workers. Robots may also reduce dis-amenities of work such as back pain and night shift visits to resident rooms, potentially reducing turnover and/or hours of work.

Consider the model of directed technology adoption and innovation developed by Acemoglu and Restrepo (2022). Although their focus is on industrial automation replacing manual production tasks in aging societies, a simple extension generates hypotheses about the service sector as well. In this model, firms produce output by combining production tasks, service tasks, and intermediates that embody the state of technology for a given industry. Production inputs are an aggregate of a unit measure of industry-specific tasks, where each task is performed either by labor or machines, and middle-aged workers specialize in production inputs. In this framework, they show that automation rotates the isocost curve (creating a

[1] Our study also relates to the literature on automation and its implications for labor share (Autor and Salomons 2018; Acemoglu and Restrepo 2019ab), as well as the emerging literature that focuses on artificial intelligence and jobs (Felten et al. 2018; Brynjolfsson et al. 2018; Webb 2020).

displacement effect) and shifts the isocost curve outwards (a productivity effect); population aging, by raising the relative scarcity and wages of middle-aged labor, spurs automation of production tasks, with an ambiguous effect on aggregate output per worker.

We hypothesize that services resemble industries that have (1) high use of middle-aged workers, but (2) relatively low technological opportunities for automation. These characteristics imply that automation in services will lag that in manufacturing, but progress more quickly in aging societies relative to their younger counterparts. More specifically, as aging puts pressure on labor markets and wages, firms and technology entrepreneurs will find it increasingly profitable to automate those tasks within the service sector that most closely resemble tasks automated in other sectors: tasks requiring the physical strength and dexterity for which middle-aged workers have a comparative advantage. Accordingly, in the service sector of aging societies, tasks involving physical strain (such as lifting frail elderly from beds to wheelchairs) will be among the first automated; and forward-planning establishments will be the first to adopt such technologies because they anticipate future demographic trends. Establishment-level employment and wages are unlikely to decrease and may increase, with sector-wide employment and wages driven by the increasing market size and lower amenability to automation of service tasks (relative to industrial production).

As noted in the text, in elderly long-term care, the parallel to production task blue collar workers are the nurses and care workers, known as "direct-care staff," performing many daily tasks requiring physical strength, stamina, and dexterity. Such service tasks also are virtually non-offshorable to countries with younger demographics, since care must take place within the local communities being served. Thus, we hypothesize that robot adoption will most directly impact employment of direct-care staff (who are indeed usually middle-aged), depending on the balance of the productivity-enhancing versus task-replacing impacts of robot adoption. In addition, we predict that larger nursing homes will adopt robots earlier than smaller homes, given the economies of scale and scope associated with these LTC robots. For example, monitoring robots are designed to cover multiple beds per room.

Our setting is similar to the healthcare and elderly care sectors of most high-income countries (including Medicare and Medicaid in the US and Germany's LTCI) in that the government regulates public LTC service prices. In the US, administered prices cover 76 percent of nursing home residents (i.e., the 62 percent of residents with Medicaid coverage and the 12 percent of residents with Medicare coverage), and these prices may vary by locality (e.g., state-specific Medicaid reimbursement rates), shaping staffing and quality; as Hackman (2019) shows in a structural model of nursing homes in one US state, increasing the Medicaid reimbursement rate increases the nurse-to-resident staffing ratio and thereby improves quality more than pro-competitive policies would in this market. In Japan, LTC prices are uniform across nursing homes. Nursing home managers are free to set wages for their employees and to hire an appropriate mix of direct-care staff within the regulated ratios (which are not binding, as discussed further below). Facilities expand and compete for residents based on location, convenience, and perceived quality of care services, shaped by local demographic trends and labor market conditions.[2]

Impacts of robot adoption on establishment-level employment and wages are theoretically ambiguous, although sector-wide employment and wages are driven by the increasing market demand and lower amenability to automation of service tasks (relative to industrial production). At the establishment level, increase in employment at robot-adopting firms would be consistent with theory of successful competition for market share and with previous empirical work on industrial firms. For example, Koch et al. (2021) find that over a 27-year period in Spain, industrial firms that were *ex ante* better-performing were those most likely to adopt manufacturing robots, leading to lower labor cost share and net job creation. (Other recent empirical studies of establishment-level robot adoption and task allocation include Bessen et al. (2019) on non-financial private firms in the Netherlands; Koch et al. (2021) who study Spanish manufacturing firms; and Acemoglu et al. (2020) and Bonfiglioli et al. (2020) who study French manufacturing.) As the large literature on the economics of healthcare and long-term care in Europe and the US Medicare and Medicaid programs demonstrates, regulated prices do not preclude competition for market share, widespread adoption of new technologies, and labor market adjustments, although “superstar firm” effects may be constrained by institutional characteristics such as the relative lack of chain firms.[3]

[2] Previous studies have underscored the importance of labor market conditions for cyclicality in formal and informal care, and its association with cyclicality in mortality rates among the elderly (e.g. Stevens et al. 2015, Mommaerts and Truskinovsky 2021)

[3] Chain ownership and for-profit organizational form for skilled nursing facilities and nursing homes are much more common in the US than in Asia or Europe.

Regarding wages, Acemoglu and Restrepo (2022) argue that "the effects of automation technologies are potentially different in countries developing these technologies in response to demographic change versus those adopting them as a result of global technological advances. In particular, Proposition 4 applies to the former set of countries and implies that demography-induced development and adoption of robots will never reduce wages" (p.13). This theory would suggest that economies like Japan that have demography-induced endogenous development and adoption of robots are unlikely to experience reduced wages from robot adoption. This theoretical prediction garners some empirical support across countries (Acemoglu and Restrepo 2022) and contributes to our conjecture that the lower wages we observe for nurses in robot-adopting nursing homes may be because of fewer night-shift hours (see discussion in main text).

Currently, qualitative evidence suggests that robots can reduce the burden on care workers, but that most tasks cannot be substituted completely. Accordingly, human care workers and robots need to coordinate and divide tasks. Anecdotal reports also hint at the potential longer-term impacts for quality of care for residents. For example, one elderly care center in Setagaya, Tokyo, that has used five types of robots since 2017—including monitoring robots to sense clients' movements in and out of bed and movement-supporting robots to enhance mobility—reported that the robots not only helped to prevent client hip problems and to reduce staff burden, but also contributed to decreasing the rate of physical accidents by 30%.[4] A government pilot study of nursing care robots in 40 nursing homes found that monitoring robots allowed for better efficiency and reduced burden for care workers; movement assistance robots (wearable and non-wearable) resulted in better prevention of hip pain in care workers, but did not change the users' satisfaction; and for nonwearable movement assistance robots, care workers said that it took time to use the robots, but led to better communication and greater safety. Managers reported that monitoring robots led to some change in inputs, since help could be provided by one staff member only, instead of multiple staff, although the time requirement did not decrease. Moreover, some indications of improved quality of life and less pain suggest that adoption of robotics could contribute to enhanced quality of care. Our study complements and extends these descriptive, anecdotal, and small-scale previous studies.

LTC Robot Subsidies

[4]https://kaigorobot-online.com/contents/52 (accessed January 22, 2019; PDF available on request).

According to the 2017 Report on Robotics in Elderly Care by the MHLW,[5] the 10 types are robots as wearable transfer aids; nonwearable transfer aids; mobility aids; toileting aids; monitoring systems; communication support; dementia therapy; rehabilitation support; medication support; and other robots. Starting in April 2013, the Ministry of Health, Labor and Welfare (MHLW) and Ministry of Economy, Trade, and Industry (METI) identified eight task areas such as transfer aid and communication for which they subsidize development of LTC robots. In October 2017, the ministries expanded to twelve the number of task and technology areas to subsidize. Our survey data covers the earlier period, ending in 2017.

Administrative process for robot subsidies. Municipal governments determine the planned number of subsidized robots in the following way. First, they ask nursing homes about their plans for adopting robots. Based on that information, they create a municipal-level plan for subsidizing care robots and submit it to the prefecture government. Upon review of such plans from all municipalities, the prefecture government creates a prefecture-level plan for subsidizing care robots and submits it to the central government. After evaluating all the prefecture plans, the central government allocates a budget to each prefecture. Note that subsidies for adopting care robots constitute a small part of the overall budgets that aim to improve local medical and nursing care delivery systems. The central government provides a lump sum budget for all programs, including care robots. Then, given the total budget to the prefecture, the prefecture government determines the amount of subsidy to be used for robot subsidies by each municipality.

Extracting data on robot subsidies. As noted in the main text section on "Prefecture-level data on robot subsidies and labor market conditions," our primary measure is the prefectural target for number of robots adopted, but we also coded information on budget funds allocated to robot subsidies and the prefecture target for number of facilities that adopt robots. We extract data from prefecture reports on how they utilize the funds distributed by the central government to improve LTC services in each prefecture. Documentation about use of these funds, called "*chiiki*

[5] http://www.techno-aids.or.jp/robot/file29/jirei2017.pdf (MHLW 2017; accessed March 24, 2022; PDF available on request).

iryo kaigo sougo kakuho kikin," is available through the MHLW at https://www.mhlw.go.jp/stf/seisakunitsuite/bunya/0000060713.html.

When prefectures do not report a planned number of robots to be subsidized but have budget funds allocated to robot subsidies or report the planned number of facilities to be subsidized, we impute the planned number of robots subsidized using the mean value of the correlation between planned number of robots and robot subsidies (or planned number of facilities) observed in the data. The imputation results in 5 prefectures (Gifu, Kochi, Kumamoto, Okayama, and Shimiane) with imputed subsidy values. Dropping the 5 prefectures in our main IV regression returns estimates that are qualitatively similar in overall staffing but larger in magnitude.

The number of prefectures that subsidize robot adoption has increased over time; as of FY2018, 36 prefectures out of 47 offer such subsidies (MHLW 2019). Starting in April 2018, the maximum amount that prefectures can cover was increased to 300,000 yen (approximately US$3,000) per robot. Separately from the prefectural government subsidies, in 2016, the central government earmarked a supplementary budget to promote adoption of robots in LTC facilities, totaling 5.3 billion yen (approximately US$53 million), with up to 3 million yen (US$30,000) per establishment.

As noted in the text, subsidies for robot adoption are part of larger subsidy programs that aim to improve LTC services in prefectures. To control for the impact of various other subsidy programs, our empirical analyses also included two variables that capture the funds distributed by the central government to improve LTC services in the prefecture, namely 1) funds to secure care workers and 2) funds to improve care facilities. Hence, we believe that the subsidy that we use as our IV primarily captures the aspects related to robot adoption, rather than the government's larger program.

We attempted to conduct the same analysis for 2018 but the instrumental variable was too weak to do so, probably because the subsidy policy rapidly spread across prefectures that reduced regional variations necessary for identification. Thus, our analysis focuses on an early phase of robot adoption in nursing homes.

Fact-Finding Survey on LTC Work

Our nursing home data comes primarily from the Fact-Finding Survey on LTC Work

("*Kaigo Roudo Jittai Chousa*") collected by the Care Work Foundation in Japan. The data was provided by the Social Science Japan Data Archive, Center for Social Research and Data Archives, Institute of Social Science, The University of Tokyo. The sample represents establishments in each of Japan's 47 prefectures, with a median of 15 custodial and 3 skilled nursing homes per prefecture, representing 9.3% of nursing homes residents in each prefecture on average (11.3% of custodial home residents, 6.3% of skilled nursing facility residents); see the prefectural distribution of homes and residents in Appendix Figure 3 panel A, comparing the sample to the universe of 7891 custodial type nursing homes and 4322 skilled nursing facilities in Japan in 2017.

Survey questions about nursing home management. The Fact-Finding Survey on LTC Work ("*Kaigo Roudo Jittai Chousa*") collected by the Care Work Foundation in Japan includes the following questions: Do you have employment regulations for non-regular workers? Do you employ or assign a human resources manager? Do you have a wage table for regular workers? Do you review non-regular workers' wages at least once a year? To reduce separation of workers and increase their retention, do you try to improve working conditions such as by reducing overtime work or making it easier to take paid leave? To increase retention do you increase wages?

Nursing home wage data and wage share. The survey asks the nursing home manager to select a representative group of employees, but of course this would not be perfect. When comparing the survey-based wage data to national averages for nursing home care workers in 2017, the survey data appears to be reasonably representative. For example, the average wage for care workers in our data, 275.6 (in 1000 yen per month), lies in between the national average wage of care workers with 10-14 years of experience (253.3) and the national average for those with 15 or more years of experience (279.2) Nursing home *wage share* is defined as wages, including salaries, unemployment insurance premiums, and social insurance premiums, divided by total revenue from long-term care services. Unfortunately, the survey does not ask about the amount of revenue *per se*, and thus we cannot construct productivity measures.

Representativeness of the survey. To provide suggestive evidence about the representativeness of the survey (given potential selection among respondents), we obtained the universe of nursing homes from *KaigoKensaku,* a website run by prefecture governments, which provides basic data on the universe of care providers. We compare our sample to the universe of such facilities for the type most likely to adopt robots (regular size custodial care nursing homes). As shown in the multiple panels of Appendix Figure 3, the distribution of size and staffing among the survey respondents is similar to those for the universe of such facilities, except that the survey sample facilities are slightly larger. According to the two-sample Kolmogorov-Smirnov test, we cannot reject the null hypothesis that they come from the same distribution, except for care levels 1 and 2 (mildest care levels) and total employment (distributions of total employees, care workers, and nurses). The latter difference is probably because the survey asks about the number of workers and residents of the establishment, which may provide multiple services including in-home care and adult day care. In contrast, the data from the website on the universe of nursing homes contains information only for residential services. To address this issue in the empirical analyses, we show robustness to controlling for the number of services provided by the facility. There are no statistically significant differences between our sample and the universe of nursing homes for several key variables: the number of overall residents per nursing home (Kolmogorov-Smirnov p-value 0.2099); number of residents with the most severe needs, care required levels 4 and 5 (p-values of 0.6048 and 0.3725, respectively); and the number of such severe-need residents as a share of the total number of residents in each nursing home (p-values of 0.3060 and 0.8566, respectively). These tests suggest, reassuringly, that the case mix of the clients served by the sample generally reflects that of the universe of custodial nursing homes in Japan.

Additional empirical analyses

2SLS results when gradually adding control variables to the facility-level regressions. For staffing, including the fixed establishment controls (region, rural/urban, facility type and corporation type) and case-mix return results close to the final results with the full set of covariates. Data constraints preclude testing whether case-mix changes with robot adoption in our data. We examined this question indirectly using data from an ongoing survey that examines Covid-19 in Japanese nursing homes. Using retrospective questions on robot adoption, we examine whether nursing homes that adopt robots have a significant change over one year in their case-mix of residents, as measured by the share of residents requiring different levels of care; we find no significant change. This result indicates that case-mix is relatively stable in our context with or without robot adoption.

Regression results for staffing and robot adoption by type of robot. As noted in the results section, we also examined the relation between staffing and robot adoption by type and the year in which the facility acquired the robot.The associations are less significant for specific types of robots given larger standard errors, although unsurprisingly the associations are strongest for the most-commonly-adopted types: monitoring and communication robots (weakly associated with regular nurse staff) and aid robots (strongly associated with non-regular nurse staff). Regarding the timing of robot adoption, we see that the positive association with staffing is of larger magnitude for the most recent robots. Nursing homes that adopted robots in 2017 have 10 to 15% more employees, with the association only significant for regular employees.

In the Appendix tables we separately examine the types of robots adopted by nursing homes and present the IV estimates. Monitoring robots are typically video devices or bed pads that use sensors to evaluate resident mobility and sleep patterns. Aid robots help care workers with lifting and transporting of residents, and mobility robots assist residents with their movements. Separate panels examine regular employees and non-regular employees. First, we can see that the instrumental variable is relevant for monitoring robots and aid robots, but not mobility robots as the small first-stage F-statistics indicate. This suggests that nursing homes use the subsidy to primarily install monitoring or aid robots. The estimates are most similar with the estimates for monitoring robots, which is the category of robot that nursing homes most commonly adopt. The increase in non-regular staffing we find is largely driven by monitoring robots and aid robots.

Limitations. Several limitations discussed in the data and empirical results sections should be kept in mind when interpreting results. For example, although the sample is the most detailed data available across all prefectures in Japan, the response rate is not 100 percent, and the selectivity of the sample may lead to an under- or over-estimate of the impact of robot adoption despite the consistency of key variables between the sample and the universe of nursing homes. Survey respondents choose which employee wages to report; further research on whether wages differ among non-responding nursing homes would be valuable. Implications for worker welfare also merit study with data on hours worked; data limitations preclude knowing the extent to which benefits from lower effective work hours (from fewer or less onerous night shifts) outweigh or compensate for changes in wages.

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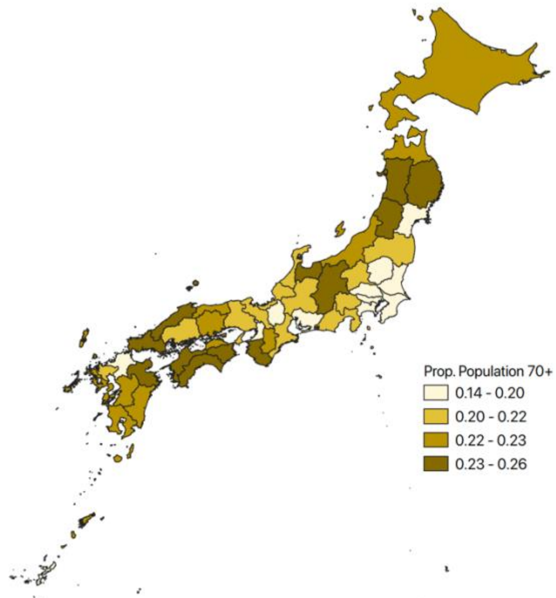
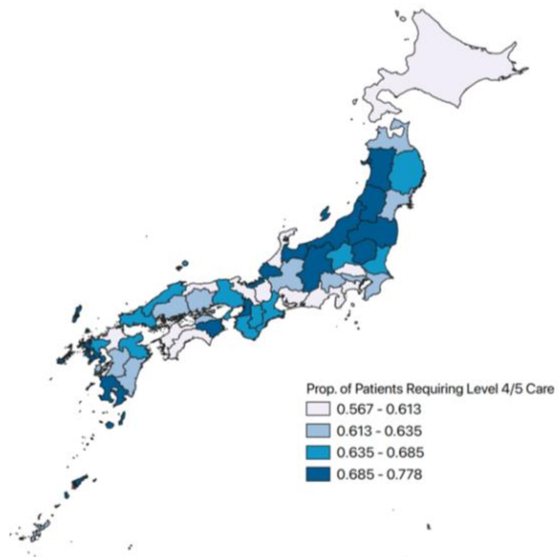
Appendix Figure 1. Demand for Long-term Care (LTC) in Japan

A. Proportion of population ages 70+

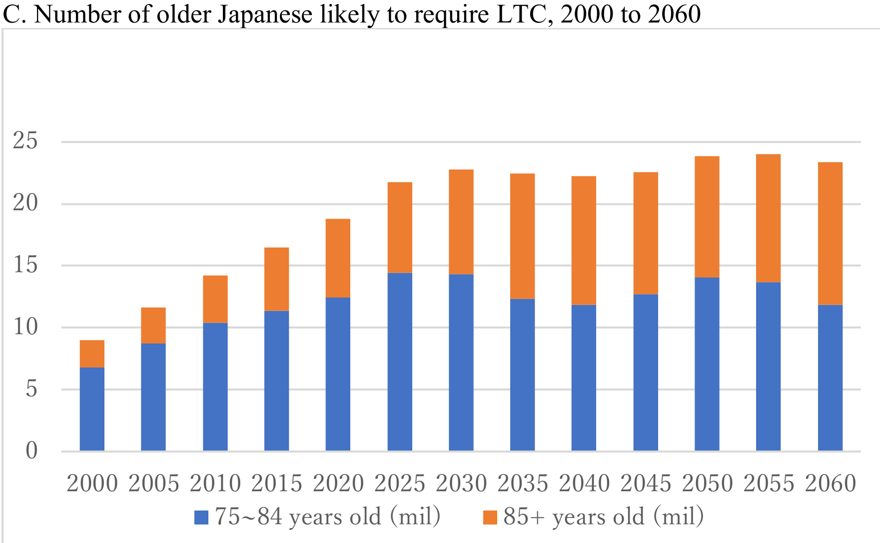


B. Proportion of nursing homes residents with substantial functional limitations (level 4/5 care)



Source: Statistical Data on Prefectures (Ministry of Internal Affairs and Communications)
Map source: GADM ver. 3.6, Center for Spatial Sciences at the University of California, Davis

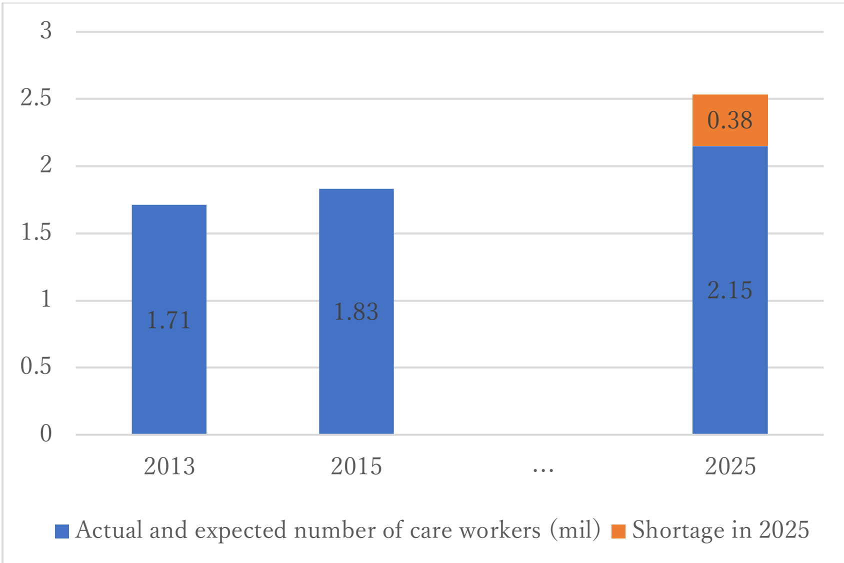
C. Number of older Japanese likely to require LTC, 2000 to 2060



Source: Population Projection for Japan (National Institute for Social Security and Population Issues), National Census (Ministry of Internal Affairs and Communications).

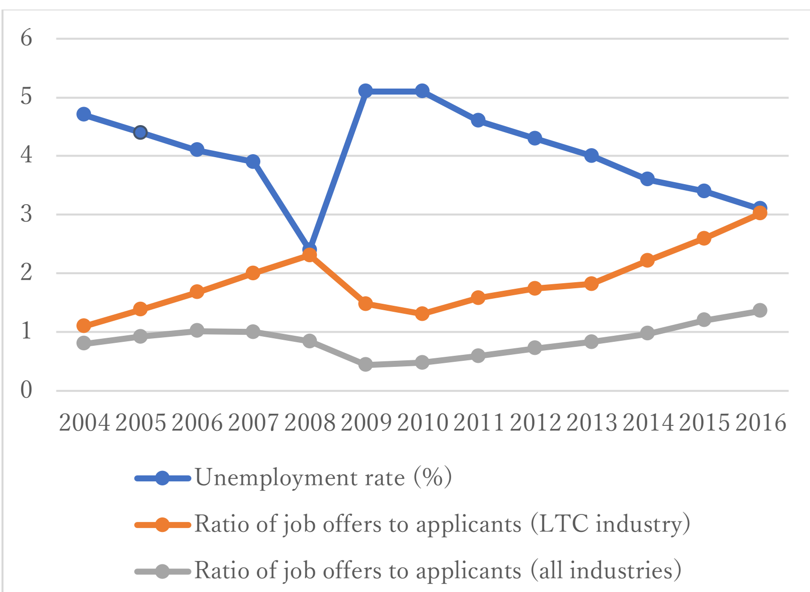
Appendix Figure 2. Supply of LTC workers and labor markets in Japan

Panel A: Actual vs. expected number of care workers



Source: MHLW (2017) (http://www.techno-aids.or.jp/robot/file29/02shiryo.pdf accessed Dec. 12, 2019)

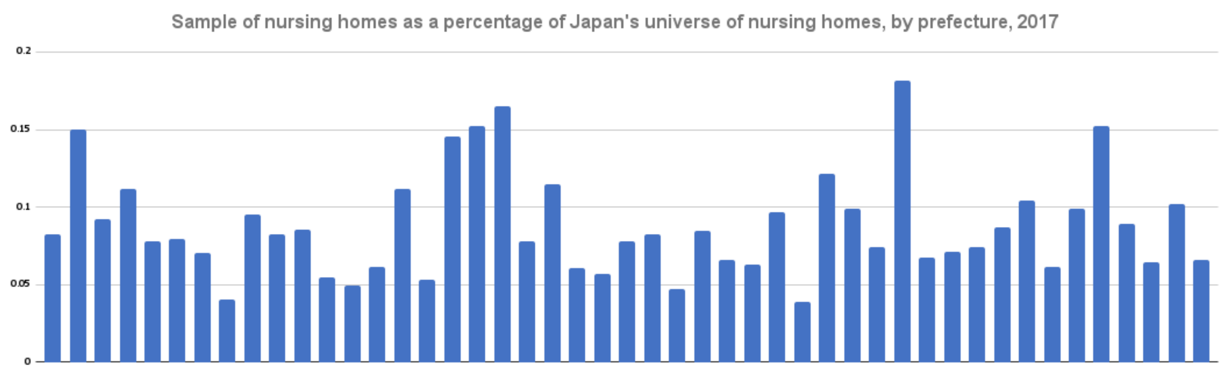
Panel B: Ratio of job offers to applicants for the LTC industry in comparison

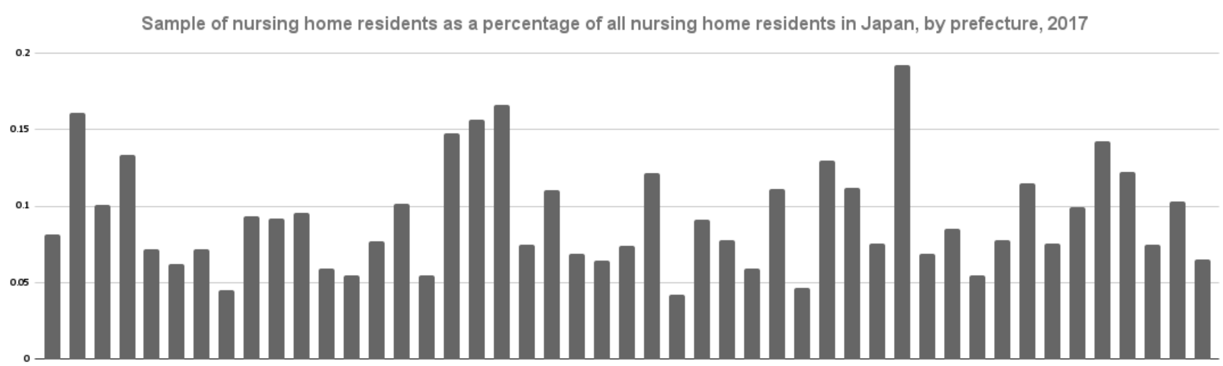


Data source: Employment Security Statistics (MHLW), Labor Force Survey (MHLW).

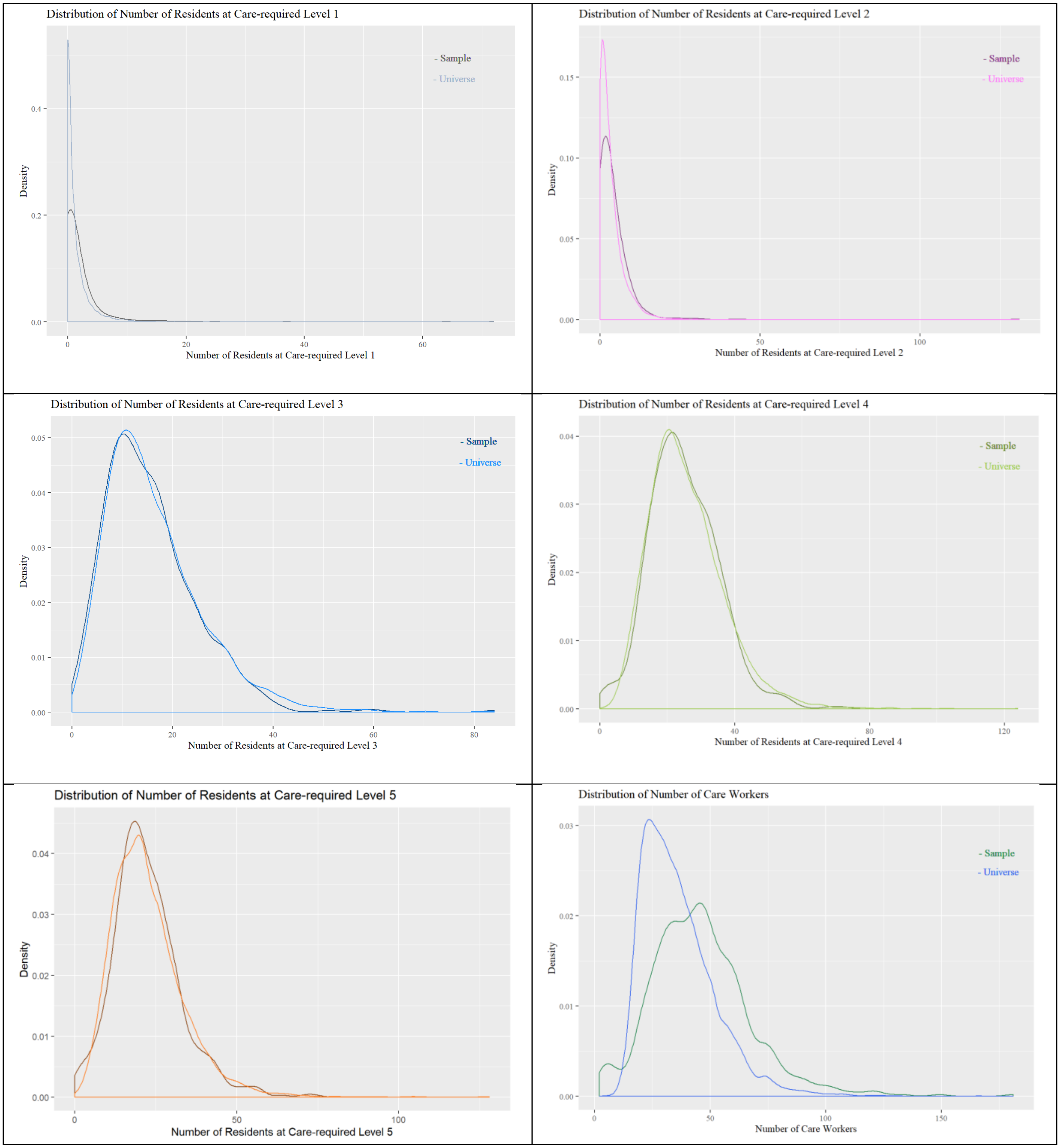
Appendix Figure 3: Distributions of nursing homes, residents, and care workers in the "Fact-Finding Survey on LTC Work" sample compared to the universe of nursing homes in Japan

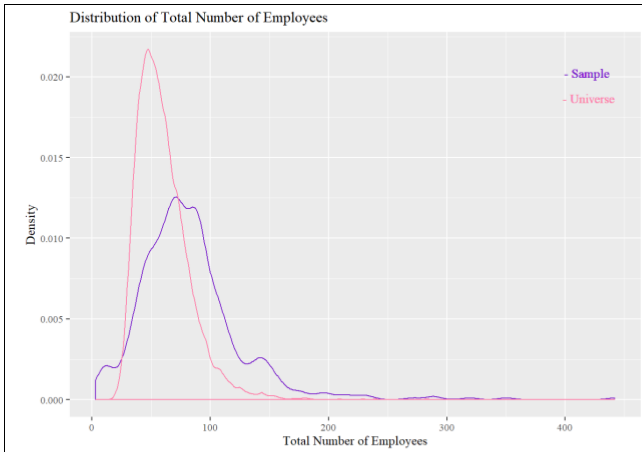
Appendix Figure 3A: Sample of custodial and skilled-nursing homes and of their residents as a percentage of all such nursing homes and their residents in Japan in 2017

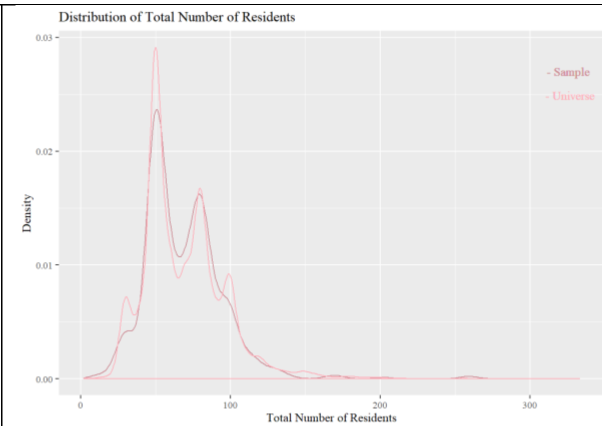




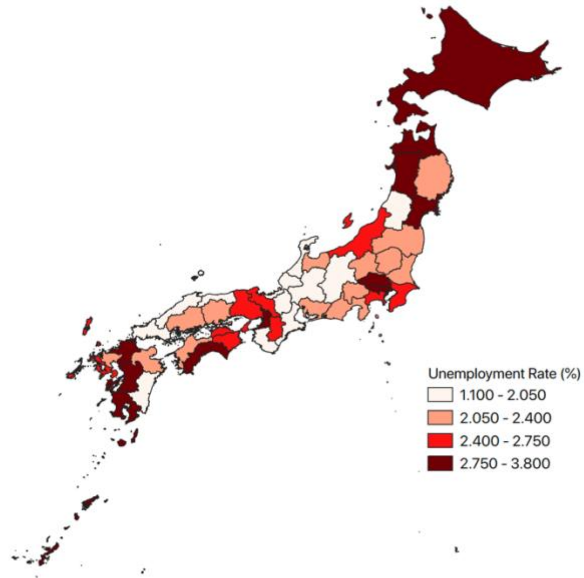
Appendix Figure 3B: Sample of nursing homes (2017-18) compared to microdata for the universe of type 23 (custodial >30 resident) nursing homes in Japan (2018-19)




Distribution of Total Number of Employees
Density
0.020
0.015
0.010
0.005
0.000
0
100
200
300
400
Total Number of Employees
- Sample
- Universe

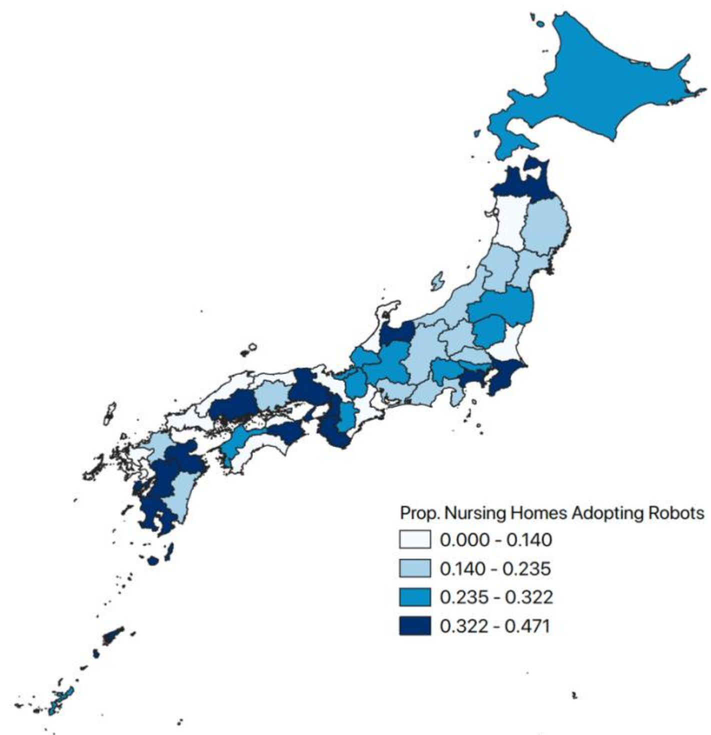

Distribution of Total Number of Residents
Density
0.03
0.02
0.01
0.00
0
100
200
300
Total Number of Residents
- Sample
- Universe

Appendix Figure 4: Unemployment rate by prefecture



Source: Statistical Data on Prefectures (Ministry of Internal Affairs and Communications)
Map source: GADM ver. 3.6, Center for Spatial Sciences at the University of California, Davis

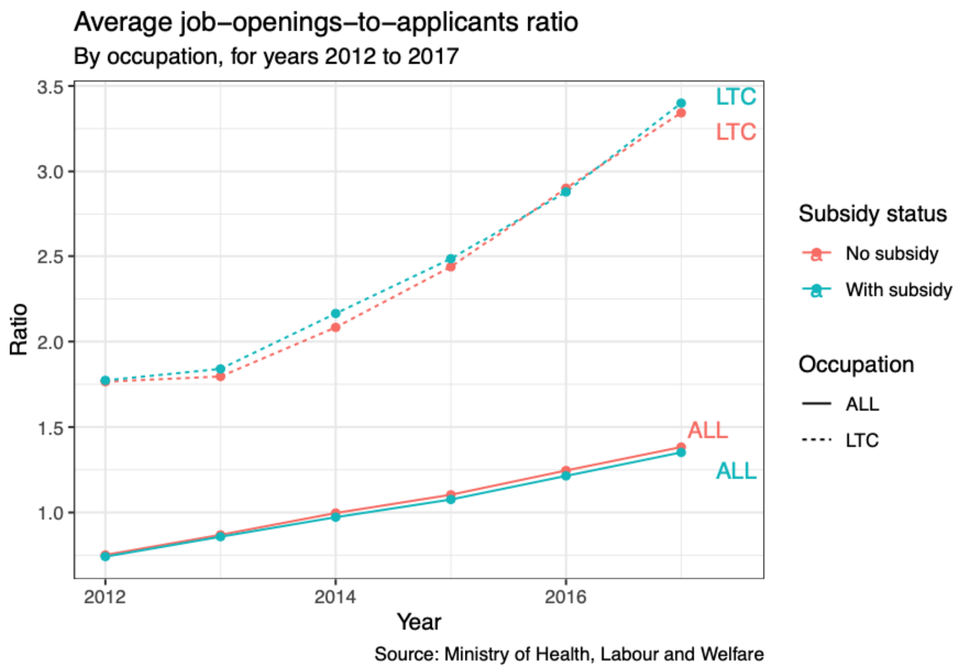
Appendix Figure 5: Map of proportion of robot adoption by prefecture



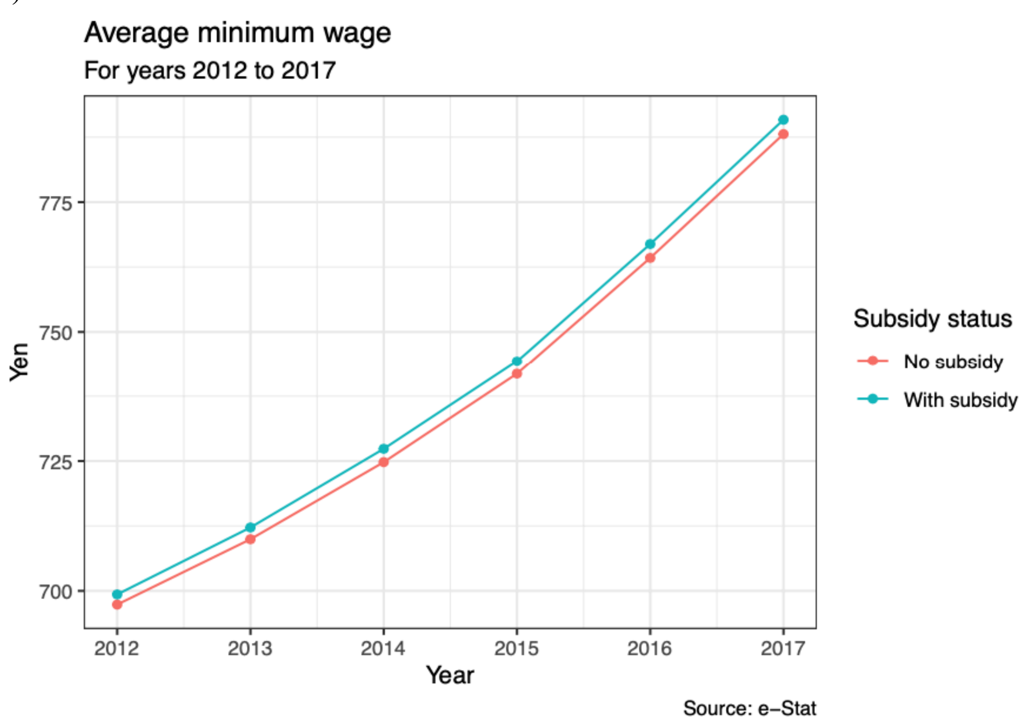
Source: LTC survey 2017
Map source: GADM ver. 3.6, Center for Spatial Sciences at the University of California, Davis

Appendix Figure 6. Labor market conditions in prefectures that subsidize robots and those that do not

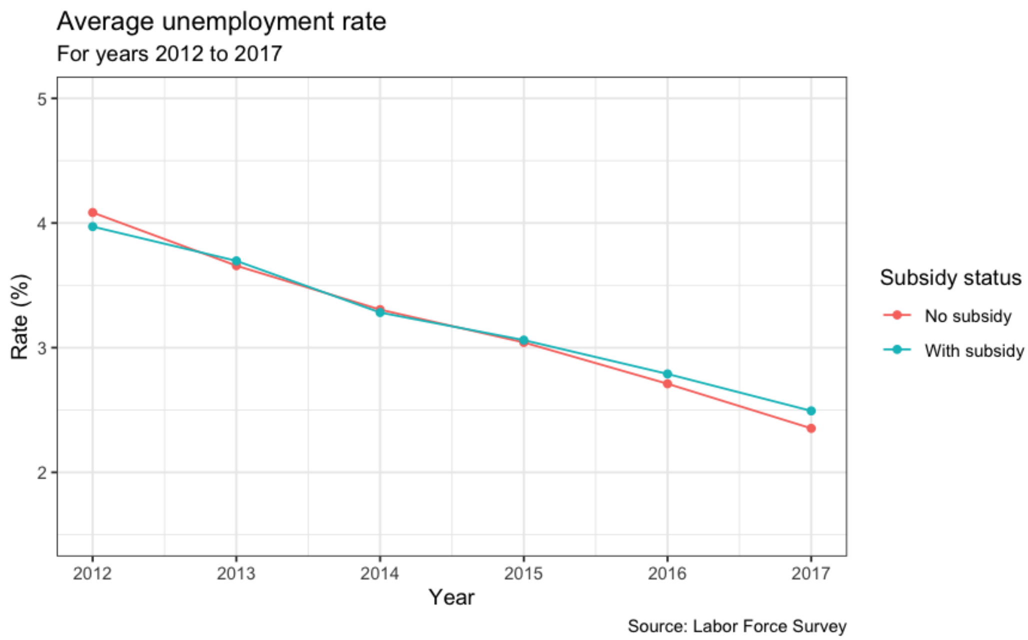
a)



b)



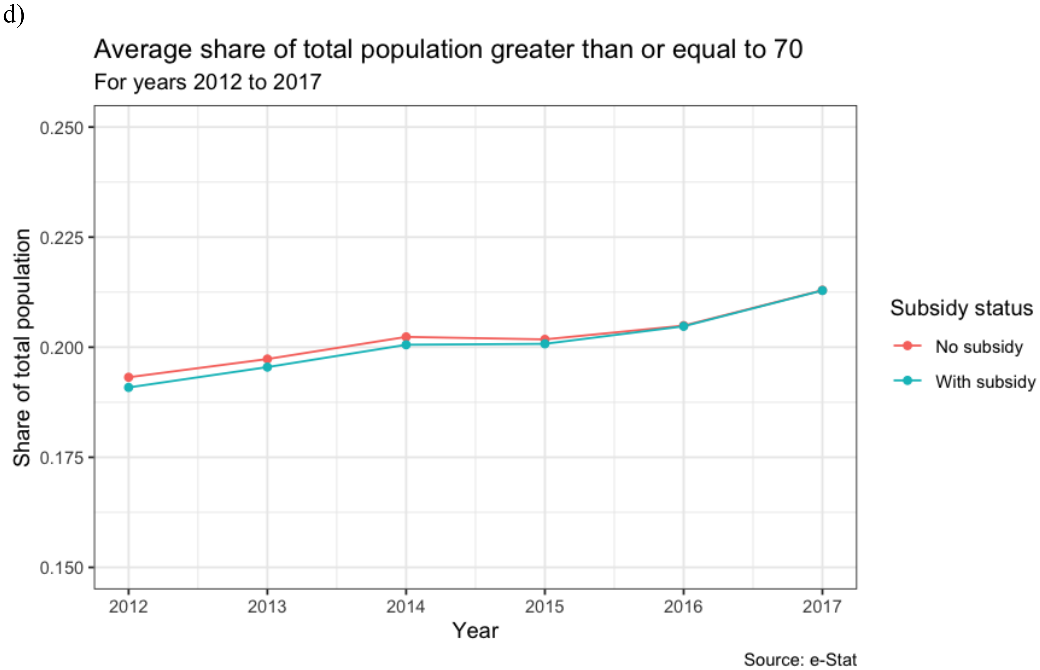
Notes: 100 Japanese Yen is approximately 1 USD.



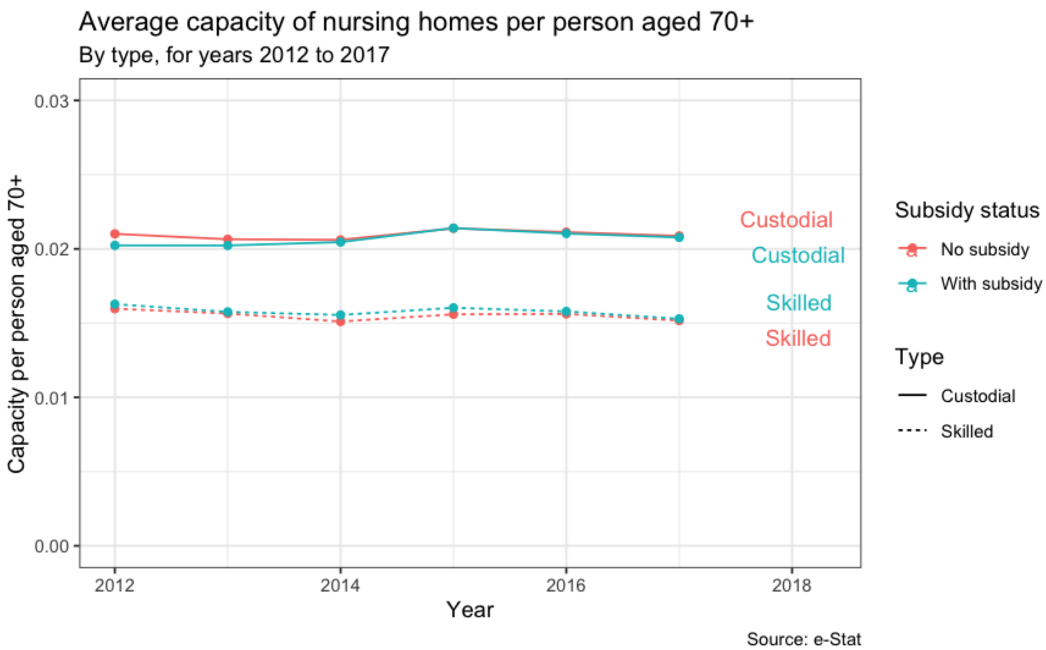
Average unemployment rate
For years 2012 to 2017
Rate (%)
5
4
3
2
2012
2013
2014
2015
2016
2017
Year
Subsidy status
No subsidy
With subsidy
Source: Labor Force Survey

c)

d)



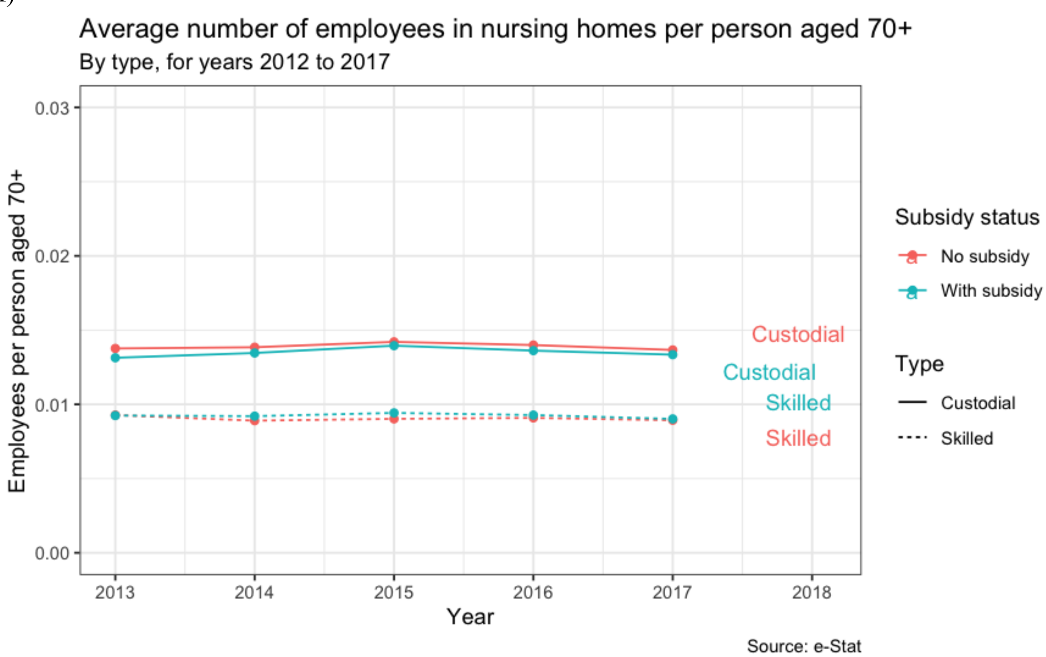
Average share of total population greater than or equal to 70
For years 2012 to 2017
Share of total population
0.250
0.225
0.200
0.175
0.150
2012
2013
2014
2015
2016
2017
Year
Subsidy status
No subsidy
With subsidy
Source: e-Stat



Average capacity of nursing homes per person aged 70+
By type, for years 2012 to 2017
Capacity per person aged 70+
0.03
0.02
0.01
0.00
2012
2014
2016
2018
Year
Custodial
Custodial
Skilled
Skilled
Subsidy status
No subsidy
With subsidy
Type
Custodial
Skilled
Source: e-Stat

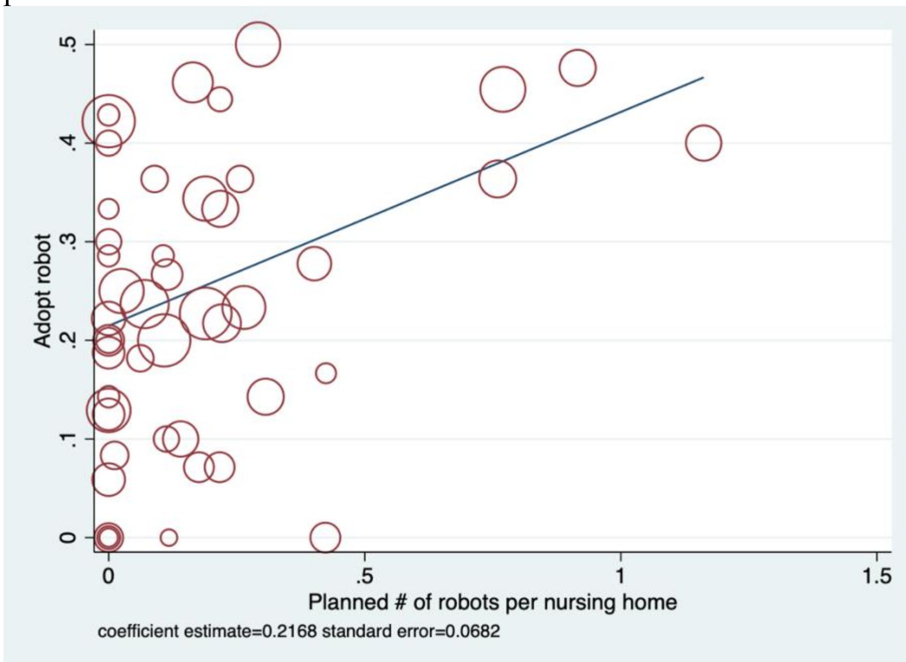
e)

f)

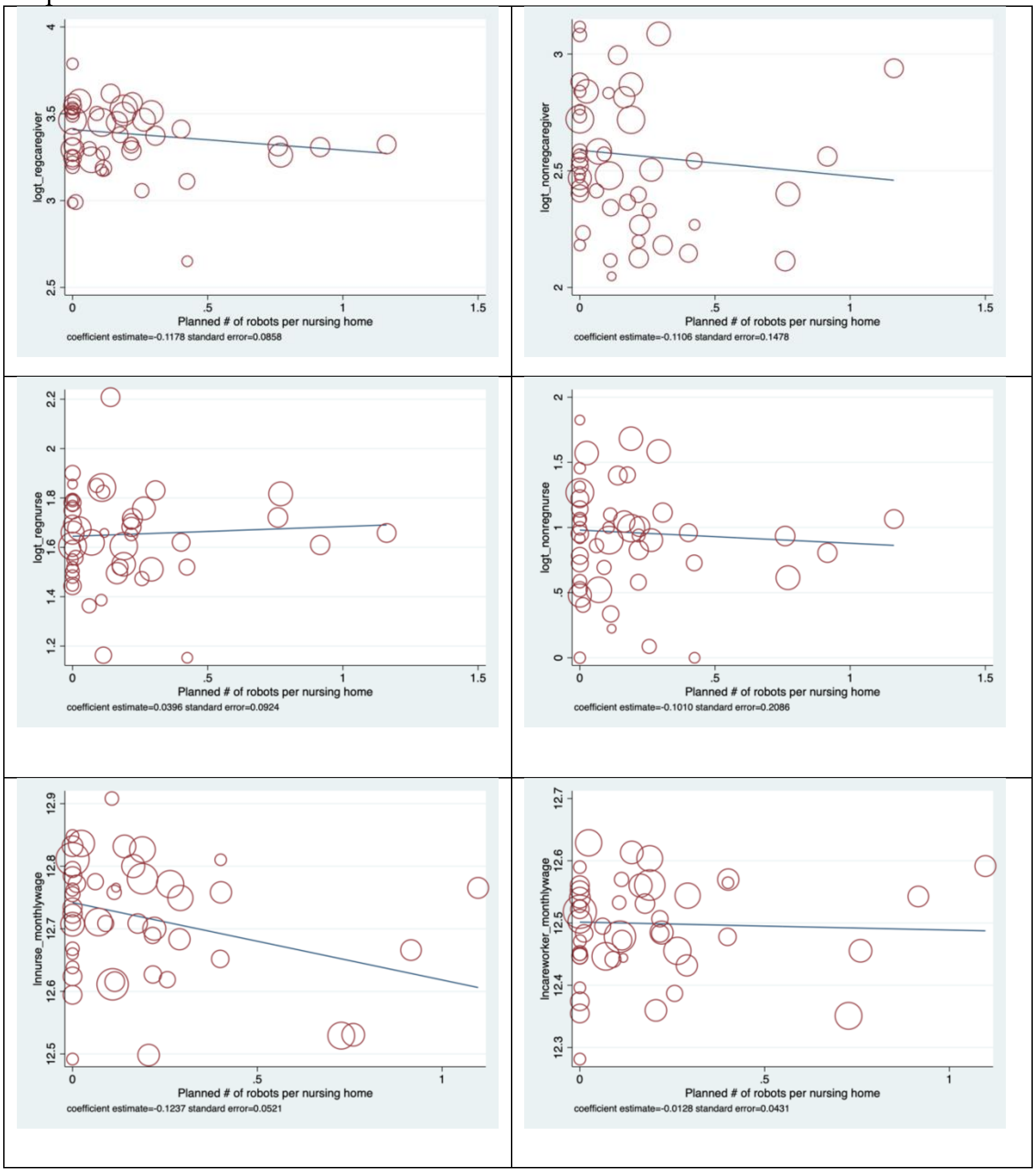


Average number of employees in nursing homes per person aged 70+
By type, for years 2012 to 2017
Employees per person aged 70+
0.03
0.02
0.01
0.00
2013
2014
2015
2016
2017
2018
Year
Custodial
Custodial
Skilled
Skilled
Subsidy status
No subsidy
With subsidy
Type
Custodial
Skilled
Source: e-Stat

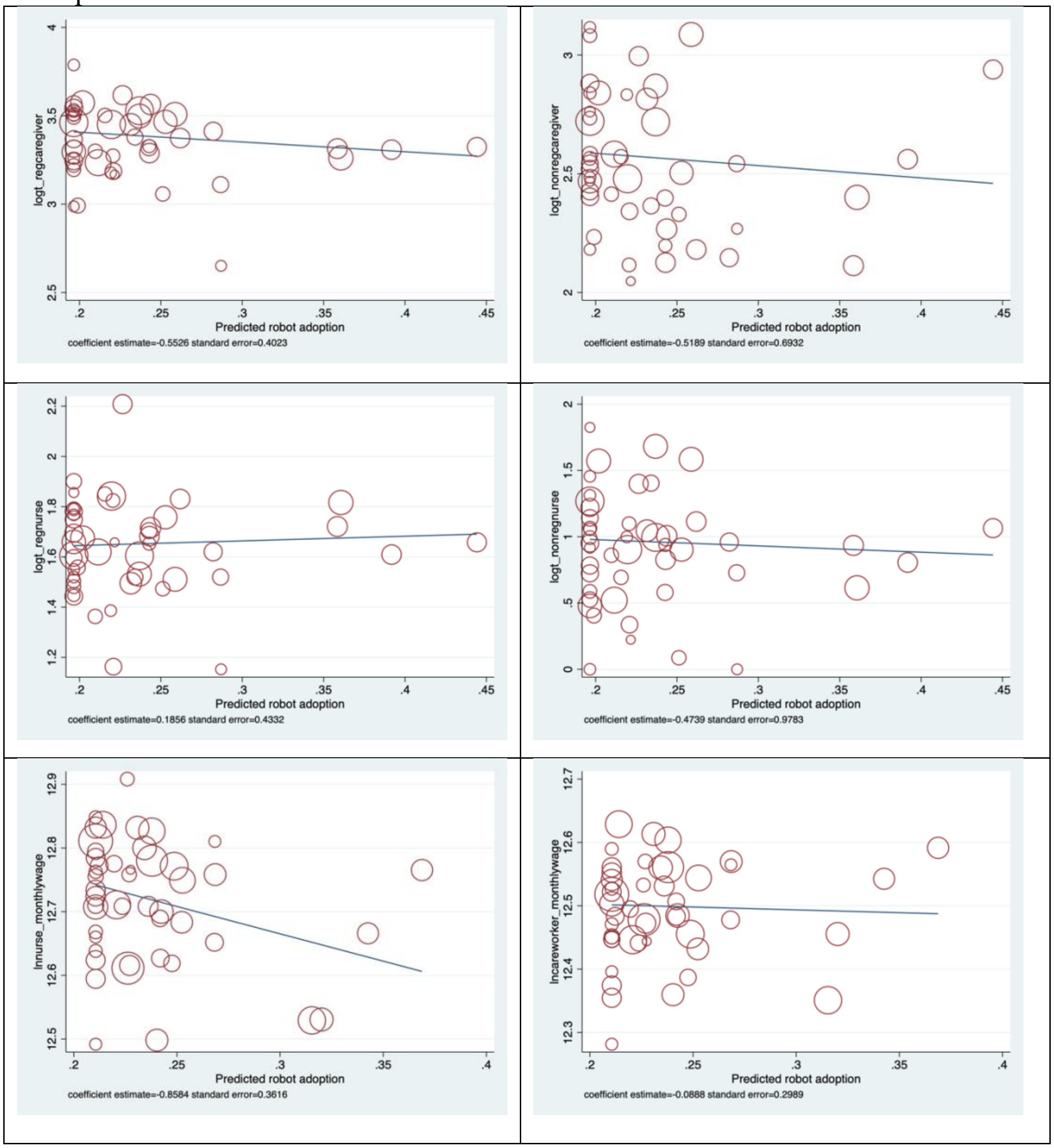
Appendix Figure 7. Scatter plot and regression line of the first-stage using data collapsed at the prefecture level



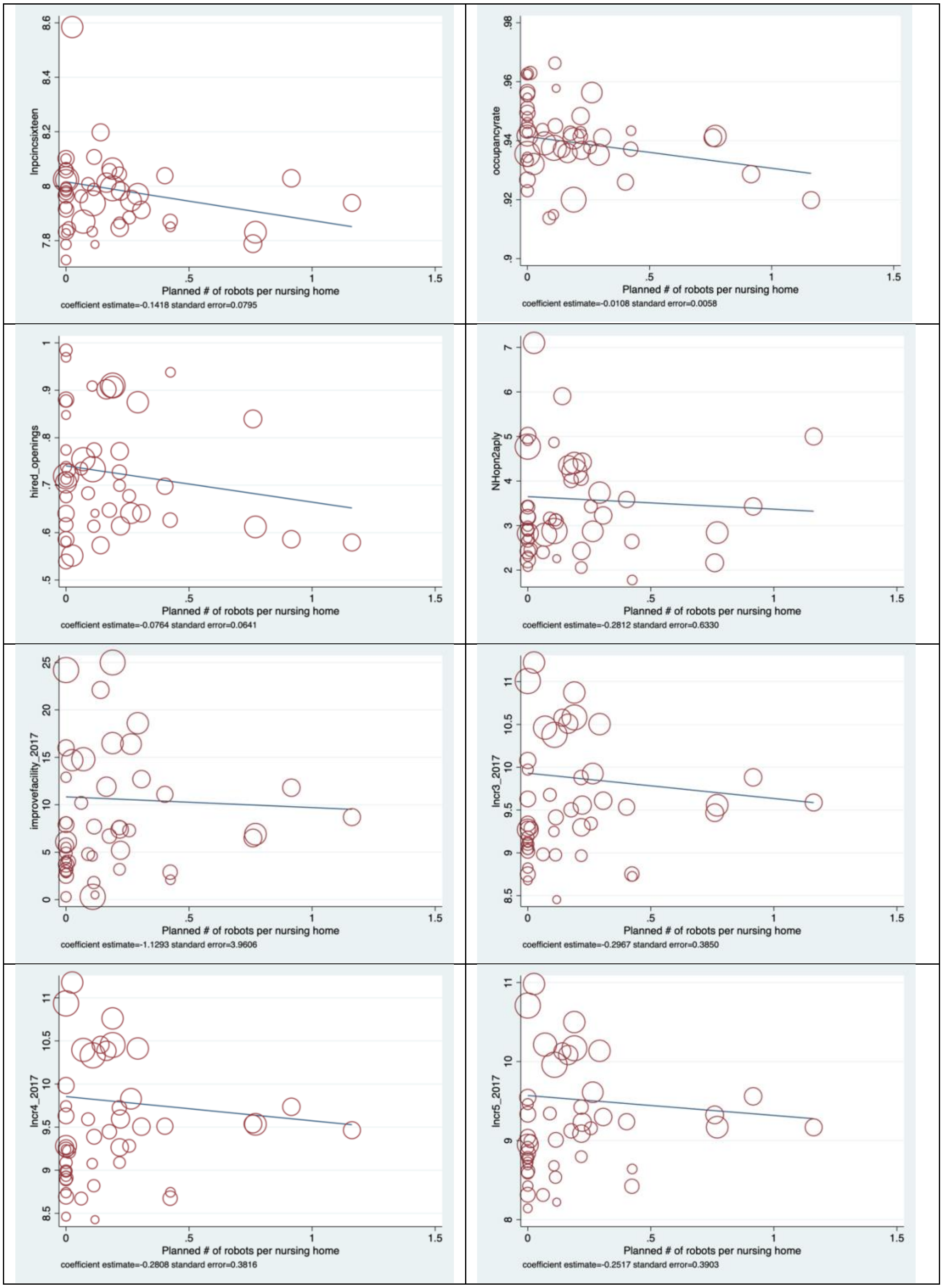
Appendix Figure 8. Scatter plots and regression lines of the reduced-form using data collapsed at the prefecture level



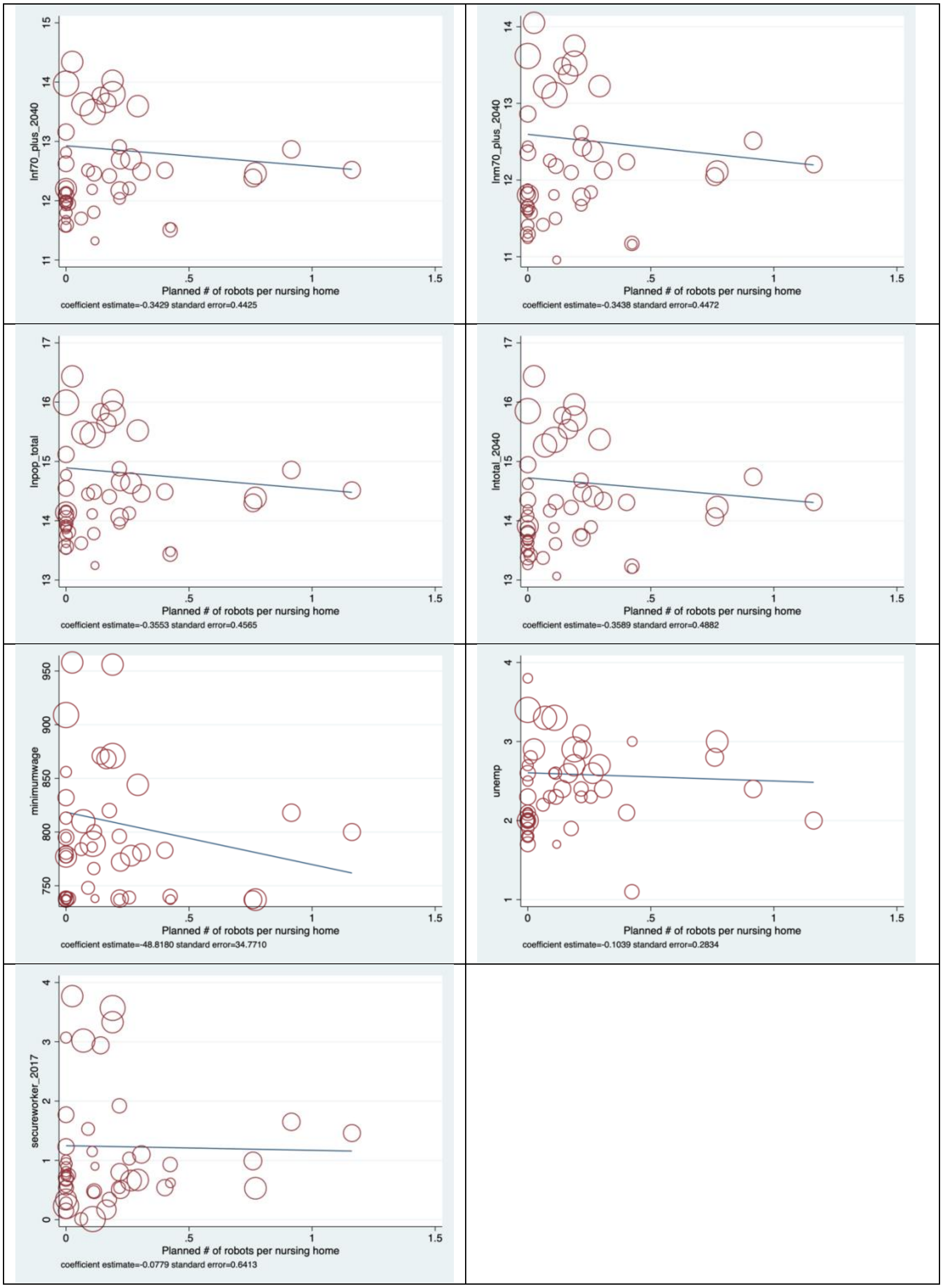
Appendix Figure 9. Scatter plots and regression lines of the second-stage when data is collapsed at the prefecture level



Appendix Figure 10. Scatter plots and regression lines for the prefecture variables and the instrumental variable



Appendix Figure 10. Scatter plots and regression lines for the prefecture variables and the instrumental variable – continued.



Appendix Table 1. Descriptive statistics by nursing home type

	Custodial nursing homes		Skilled nursing homes		Custodial and skilled nursing homes	
	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error
Adopt robots	0.262	0.016	0.230	0.031	0.256	0.014
Adopt aid robots	0.082	0.010	0.063	0.018	0.078	0.009
Adopt mobility robots	0.051	0.008	0.047	0.015	0.050	0.007
Adopt monitoring and communication robots	0.178	0.014	0.136	0.025	0.170	0.012
Number of care workers	42.612	0.786	40.738	1.381	42.230	0.687
Number of nurses	6.585	0.148	13.277	0.385	7.948	0.166
Number of total staff	75.435	1.600	98.545	8.406	80.141	2.152
Number of care workers - regular employees	28.888	0.574	31.408	1.075	29.401	0.507
Number of nurses - regular employees	4.099	0.119	9.686	0.320	5.237	0.136
Number of total staff - regular employees	48.003	1.046	73.346	6.438	53.163	1.586
Number of residents	62.173	0.993	89.204	2.544	67.677	1.010
Care workers per resident	0.746	0.023	0.487	0.025	0.693	0.019
Nurses per resident	0.115	0.003	0.165	0.009	0.125	0.003

Appendix Table 2. Descriptive statistics by nursing home location

	Metropolis		Urban		Rural	
	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error
Adopt robots	0.287	0.038	0.248	0.017	0.256	0.033
Adopt aid robots	0.077	0.022	0.074	0.011	0.087	0.022
Adopt mobility robots	0.077	0.022	0.043	0.008	0.052	0.017
Adopt monitoring and communication robots	0.189	0.033	0.166	0.015	0.169	0.029
Number of care workers	48.937	1.526	42.193	0.879	36.820	1.406
Number of nurses	9.874	0.611	7.752	0.185	7.081	0.315
Number of total staff	92.252	4.771	81.407	2.948	65.640	2.642
Number of care workers - regular employees	34.329	1.282	29.414	0.627	25.192	1.092
Number of nurses - regular employees	6.112	0.540	5.166	0.145	4.791	0.266
Number of total staff - regular employees	60.888	3.684	54.013	2.156	43.628	2.030
Number of residents	84.636	3.099	65.994	1.183	59.698	1.914
Care workers per resident	0.631	0.022	0.715	0.028	0.668	0.031
Nurses per resident	0.121	0.006	0.125	0.003	0.130	0.009

Notes: Japanese nursing homes are largest in the main metropolises, smaller in other urban areas, and smallest in rural areas. For example, the total number of residents averages 85 in metro areas, 66 in other urban areas, and 60 in rural areas (see Appendix Table 2). Unsurprisingly, the larger urban nursing homes are also more likely to adopt robots (28.7%), compared to 25% in other urban or rural nursing homes. Perhaps more surprisingly, the number of care workers and nurses per resident is slightly higher in rural compared to urban nursing homes, on average (see Appendix Table 2). The staffing composition as measured by percentage regular workers is very similar across urban or rural location, with the exception of nurses: metropolitan nursing homes have a lower share of regular nurses (62%) compared to other urban and rural nursing homes (67%).

Appendix Table 3. Average wage of care workers and nurses (in Japanese yen)

	Mean	Std. Dev.	Min	Max	Obs
All employees					
Care workers (monthly)	275,627	67,483	114,710	633,274	8,263
Nurses (monthly)	342,044	80,309	122,333	710,233	1,595
Manager (monthly)	576,028	390,100	121,750	5,065,000	809
Care workers (hourly)	965	279	715	6,400	1,991
Nurses (hourly)	1,398	287	780	2,400	245
Regular employees					
Care workers (monthly)	280,986	65,821	114,710	633,274	7,652
Nurses (monthly)	346,346	78,288	127,000	710,233	1,508
Non-regular employees					
Care workers (hourly)	965	281	715	6,400	1,953
Nurses (hourly)	1,398	288	780	2,400	236
Minimum wage (hourly)	902				

Note: The minimum wage noted above is the national weighted average. In Japan, the minimum wage is determined by the hour and at the prefecture level.

Appendix Table 4. Prefecture characteristics and whether prefectures subsidize nursing care robots

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: Subsidize robot				
		Parsimonious		*Includes LTC vars.*	
Log(per capita income)	−1.924	−1.084*	−1.534*	−1.618	−1.408
	(1.206)	(0.621)	(0.903)	(1.179)	(1.234)
Unemployment rate	0.373			0.342	0.33
	(0.251)			(0.243)	(0.247)
Log(total population)	−1.939	−0.506	−4.521	-2.016	−1.501
	(6.827)	(0.755)	(0.903)	(6.597)	(6.717)
Log(population 70 or older)	0.677	0.785	2.451	0.456	0.167
	(2.739)	(0.813)	(1.605)	(2.650)	(2.715)
Minimum wage	0.002			−0.006	−0.005
	(0.005)			(0.006)	(0.007)
Log(number of nursing homes)	1.531*			1.14	1.137
	(0.807)			(0.814)	(0.823)
Occupancy rate of nursing homes	−5.120			−0.825	−2.820
	(7.542)			(7.720)	(8.365)
Jobs hired per opening	−0.620			−0.572	−0.690
	(0.951)			(0.919)	(0.946)
NH openings to applicants	0.079			−0.046	0.209
	(0.139)			(0.153)	(0.414)
Log (Number of people certified for care level 3)	−0.226			−0.433	−0.523
	(1.362)			(1.322)	(1.344)
Log (Number of people certified for care level 4)	−3.721*			−3.105	−2.865
	(1.899)			(1.871)	(1.927)
Log (Number of people certified for care level 5)	1.780			1.874	1.648
	(1.237)			(1.197)	(1.257)
Subsidies for securing workers	0.026			0.090	0.079
	(0.110)			(0.113)	(0.116)
Subsidies for improving facilities	−0.007			−0.008	−0.006
	(0.021)			(0.020)	(0.021)
Log (Estimated population in 2040)	1.952		1.818	1.905	1.384
	(2.844)		(2.154)	(2.748)	(2.888)
Log (Estimated male over 70 in 2040)	2.956		3.788*	1.422	1.491
	(2.977)		(2.055)	(3.017)	(3.053)
Log (Estimated female over 70 in 2040)	−3.047		−3.206	−1.165	−0.878
	(4.737)		(3.775)	(4.712)	(4.785)
Perception on shortage of care workers	−2.203			−2.305	−2.243
	(1.528)			(1.478)	(1.497)
Perception on shortage of nurses	0.201			0.163	0.331
	(1.324)			(1.279)	(1.318)
Difficulty of hiring high-quality workers	1.014			0.775	0.733
	(0.954)			(0.933)	(0.945)
Monthly wage for regular, full time LTC workers				0.031	0.028
				(0.018)	(0.019)
Job-openings-to-applicants ratio for LTC workers					−0.304
					(0.458)
Observations	47	47	47	47	47
R-squared	0.445	0.116	0.189	0.501	0.51
F-statistic	1.041	1.885	1.556	1.197	1.137
	(df = 20; 26)	(df = 3; 43)	(df = 6; 40)	(df = 21; 25)	(df = 22; 24)
p-value	0.455	0.146	0.185	0.3306	0.3779

Appendix Table 5. Robot adoption

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Dependent variable: Adopt robot								
			Other technology	*Management practices*	*Prefecture variables*	*Additional facility variables*	*Perceptions of labor shortage*	*Subsidy*	
Planned number of robots per nursing home in 2017								0.423***	0.428***
								(0.0892)	(0.0896)
Skilled nursing home	0.0323	0.0926	0.0855	0.0965	0.0804	0.0735	0.0637	0.0232	0.0690
	(0.0628)	(0.0660)	(0.0667)	(0.0682)	(0.0698)	(0.0717)	(0.0747)	(0.0659)	(0.0706)
Log(number of residents)	0.0983***							0.0661*	
	(0.0306)							(0.0340)	
Log(care level 1~3 residents)		-0.00246	-0.00728	-0.0105	-0.00816	-0.0111	-0.0104		-0.0105
		(0.0249)	(0.0247)	(0.0247)	(0.0248)	(0.0262)	(0.0264)		(0.0262)
Log(care level 4 residents)		0.0320	0.0191	0.0133	0.0201	0.0222	0.0245		0.0400
		(0.0359)	(0.0357)	(0.0356)	(0.0354)	(0.0361)	(0.0363)		(0.0361)
Log(care level 5 residents)		0.0591**	0.0510*	0.0536*	0.0460	0.0344	0.0283		0.0278
		(0.0301)	(0.0308)	(0.0306)	(0.0308)	(0.0319)	(0.0327)		(0.0324)
Wheel chair lifts			0.0730**	0.0695**	0.0740**	0.0863***	0.0774**	0.0805**	0.0800**
			(0.0321)	(0.0317)	(0.0322)	(0.0333)	(0.0338)	(0.0341)	(0.0341)
Adjustable beds			-0.0785	-0.0856	-0.0970*	-0.122**	-0.138**	-0.147**	-0.153***
			(0.0573)	(0.0561)	(0.0537)	(0.0563)	(0.0566)	(0.0579)	(0.0575)
Seat lifting wheel chair			0.0190	-0.00227	-0.00380	0.0164	0.0176	0.0180	0.0167
			(0.0517)	(0.0516)	(0.0502)	(0.0532)	(0.0528)	(0.0519)	(0.0520)
Special bathtub			0.0141	0.0124	0.0204	0.00470	-0.0105	-0.0149	-0.0148
			(0.0390)	(0.0385)	(0.0394)	(0.0407)	(0.0426)	(0.0419)	(0.0419)
Stretcher			0.0557	0.0550	0.0599	0.0575	0.0770*	0.0846*	0.0809*
			(0.0445)	(0.0443)	(0.0444)	(0.0472)	(0.0463)	(0.0464)	(0.0464)
Wheel chair for showers			0.0245	0.0261	0.0296	0.0282	0.0263	0.0292	0.0285
			(0.0316)	(0.0318)	(0.0320)	(0.0331)	(0.0336)	(0.0331)	(0.0331)
Wheel chair scale			0.165***	0.154***	0.152***	0.145***	0.158***	0.153***	0.149***
			(0.0373)	(0.0371)	(0.0373)	(0.0383)	(0.0391)	(0.0406)	(0.0403)
Has employment regulation for non-regular workers				-0.0515	-0.0500	-0.0165	-0.0114	-0.0229	-0.0241
				(0.0551)	(0.0553)	(0.0604)	(0.0618)	(0.0616)	(0.0615)
Has a HR manager				0.0567*	0.0644**	0.0457	0.0634**	0.0739**	0.0737**
				(0.0297)	(0.0297)	(0.0311)	(0.0315)	(0.0312)	(0.0311)
Has a wage table				0.00704	0.0127	0.0265	0.0232	0.0248	0.0231
				(0.0504)	(0.0508)	(0.0537)	(0.0553)	(0.0538)	(0.0537)
Improve working conditions for retention				-0.0213	-0.0177	-0.0227	-0.0258	-0.0206	-0.0236
				(0.0293)	(0.0294)	(0.0304)	(0.0309)	(0.0304)	(0.0305)
Improve wages for retention				0.0919***	0.0903***	0.0830***	0.0836***	0.0891***	0.0901***
				(0.0291)	(0.0291)	(0.0303)	(0.0309)	(0.0305)	(0.0305)
Additional Provider Payment				-0.00409	-0.0141	-0.0253	-0.0135	-0.0253	-0.0296
				(0.0726)	(0.0723)	(0.0777)	(0.0776)	(0.0788)	(0.0787)
Log(per capita income)					0.172	0.116	0.131	0.636**	0.649**
					(0.266)	(0.276)	(0.282)	(0.287)	(0.288)
Unemployment rate					0.0731	0.0880	0.0412	-0.0134	-0.00871
					(0.0764)	(0.0798)	(0.0826)	(0.0820)	(0.0825)
Log(total population)					-1.557	-1.636	-0.531	-1.937	-1.949
					(1.413)	(1.465)	(1.485)	(1.494)	(1.488)
Log(population 70 or older)					-0.576	-0.642	-1.059	-0.331	-0.291
					(0.699)	(0.727)	(0.733)	(0.739)	(0.740)
Minimum wage					0.00143	0.00151	0.00201	0.00101	0.00101
					(0.00129)	(0.00134)	(0.00135)	(0.00136)	(0.00136)
Log(number of nursing homes)					0.0834	0.125	0.145	-0.250	-0.251
					(0.212)	(0.219)	(0.222)	(0.234)	(0.235)
Occupancy rate of nursing homes					-5.757***	-5.759***	-7.206***	-3.356	-3.386
					(1.995)	(2.116)	(2.236)	(2.368)	(2.384)

Jobs hired per opening					0.299	0.300	0.146	0.382	0.394
					(0.269)	(0.280)	(0.286)	(0.285)	(0.285)
NH job openings per applicants					0.0330	0.0509	0.0160	-0.0289	-0.0290
					(0.0364)	(0.0391)	(0.0404)	(0.0402)	(0.0404)
Log (Number of people certified for care level 3)					-0.232	-0.214	-0.229	-0.118	-0.122
					(0.296)	(0.310)	(0.313)	(0.306)	(0.309)
Log (Number of people certified for care level 4)					-0.0524	-0.137	0.279	0.858	0.835
					(0.506)	(0.524)	(0.560)	(0.552)	(0.554)
Log (Number of people certified for care level 5)					0.524	0.539	0.275	-0.268	-0.286
					(0.338)	(0.350)	(0.370)	(0.368)	(0.371)
Subsidies for securing workers					-0.0644***	-0.0647***	-0.0726***	-0.0780***	-0.0773***
					(0.0203)	(0.0209)	(0.0217)	(0.0216)	(0.0215)
Subsidies for improving facilities					0.00937**	0.00939**	0.0120**	0.0130***	0.0131***
					(0.00460)	(0.00472)	(0.00483)	(0.00475)	(0.00474)
Log (Estimated population in 2040)					0.413	0.390	-0.260	0.404	0.441
					(0.727)	(0.749)	(0.773)	(0.773)	(0.771)
Log (Estimated male over 70 in 2040)					-0.0884	-0.0137	-0.375	-0.507	-0.578
					(0.822)	(0.851)	(0.865)	(0.834)	(0.846)
Log (Estimated female over 70 in 2040)					1.356	1.436	1.648	2.073*	2.119*
					(1.026)	(1.066)	(1.086)	(1.078)	(1.082)
Training for regular care workers						0.101**	0.0991**	0.103**	0.105**
						(0.0492)	(0.0495)	(0.0490)	(0.0492)
Training for new regular care workers						-0.000503	0.00891	0.00912	0.00616
						(0.0444)	(0.0453)	(0.0445)	(0.0450)
Training for non-regular care workers						-0.0995**	-0.0999**	-0.102**	-0.102**
						(0.0451)	(0.0458)	(0.0456)	(0.0457)
Training for new non-regular care workers						0.0726	0.0646	0.0612	0.0623
						(0.0443)	(0.0457)	(0.0453)	(0.0454)
Perception on shortage of care workers							0.193	0.201	0.197
							(0.189)	(0.186)	(0.186)
Perception on shortage of nurses							0.317*	0.237	0.237
							(0.170)	(0.166)	(0.166)
Difficulty of hiring high-quality workers							-0.00360	-0.0944	-0.103
							(0.185)	(0.182)	(0.181)
Observations	938	938	938	934	934	884	857	857	857
R-squared	0.029	0.032	0.054	0.069	0.100	0.113	0.127	0.153	0.154

Notes: All regressions additionally control for years of operation, location (metropolis, urban, rural), corporation type (social council, social organization, medical facility, local government facility, and other), region fixed effects (we divide Japan into 6 regions), and a dummy for skilled nursing homes. Standard errors clustered by prefecture are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table 6. Robot adoption, staffing, and wages – IV Estimates by level of control variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	All employees		Regular employees		Non-regular employees						
VARIABLES	Log(number of care workers)	Log(number of nurses)	Log(number of care workers)	Log(number of nurses)	Log(number of care workers)	Log(number of nurses)	Log(monthly wage) - care workers	Log(hourly wage) - care workers	Log(monthly wage) - nurses	Log(hourly wage) - nurses	Log(monthly wage) - managers
Panel A. No controls											
Adopt robots	-0.469	-0.0344	-0.520	0.214	-0.211	-0.343	-0.103	-0.297*	-0.794	-0.374*	0.283
	(0.375)	(0.231)	(0.324)	(0.289)	(0.768)	(0.541)	(0.307)	(0.163)	(0.484)	(0.192)	(0.245)
First stage F-statistic	15.529						9.16	12.78	8.97	16.34	17.29
Panel B. Prefecture controls											
Adopt robots	-0.112	0.0544	-0.291	-0.176	0.574**	0.450	0.0634	-0.0678	-0.311**	-0.0447	0.189
	(0.155)	(0.172)	(0.222)	(0.171)	(0.260)	(0.312)	(0.0957)	(0.0700)	(0.136)	(0.118)	(0.182)
First stage F-statistic	38.742						29.91	27.85	24.07	4.21	30.35
Panel C. Prefecture and fixed establishment controls											
Adopt robots	-0.0451	0.166	-0.491***	-0.255**	0.938***	0.681**	-0.0248	-0.0878	-0.316***	0.111	0.0996
	(0.108)	(0.149)	(0.170)	(0.122)	(0.143)	(0.300)	(0.0665)	(0.0577)	(0.0887)	(0.317)	(0.110)
First stage F-statistic	57.165						43.96	62.16	47.11	1.11	44.09
Panel C2. Prefecture and fixed establishment controls including case-mix											
Adopt robots	0.284**	0.442**	-0.192	-0.0546	1.419***	1.004**					
	(0.113)	(0.166)	(0.191)	(0.144)	(0.291)	(0.388)					
First stage F-statistic	62.652										
Panel E. Prefecture, fixed establishment, and time-varying establishment controls											
Adopt robots	0.278***	0.388***	-0.0780	-0.000824	1.062***	0.784***	-0.0291	-0.0599	-0.269***	0.0592	0.182
	(0.0737)	(0.125)	(0.121)	(0.115)	(0.167)	(0.264)	(0.0487)	(0.0523)	(0.0702)	(0.122)	(0.115)
First stage F-statistic	73.486						61.858	75.554	48.92	5.425	54.983
Observations	857						6,805	1,685	1,307	202	650

Notes: Worker characteristics control for gender, age, age squared, experience, experience squared, and qualification level of the worker. Base facility characteristics control for years of operation, location (metropolis, urban, rural), corporation type, and skilled nursing homes. Resident case-mix controls for the log number of resident with care levels 1-3, 4, and 5. Other technology adoption controls for each non-robot technology used in the nursing homes. Management practices control for human resource management practices. Prefecture characteristics controls for the demographic and economic conditions. HR development practices control for human resource development practices in a facility. Labor shortage perceptions control for labor shortage perceptions on careworkers, nurses, and laborers in general. Standard errors clustered by prefecture are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 7. Robot adoption and change in case-mix of residents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Change in share of residents with care level						
VARIABLES	Care level 1	Care level 2	Care level 3	Care level 4	Care level 5	Care level 1,2,3	Care level 4,5
Panel A. No controls							
Adopt robots	0.00642	0.00466	-0.0175	-0.0153	0.0217	-0.00639	0.00639
	(0.0107)	(0.0126)	(0.0147)	(0.0162)	(0.0193)	(0.0275)	(0.0275)
Observations	805	805	805	805	805	805	805
R-squared	0.001	0.000	0.001	0.001	0.001	0.000	0.000
Panel B. With prefecture controls							
Adopt robots	0.00695	0.00532	-0.0189	-0.0147	0.0213	-0.00660	0.00660
	(0.0109)	(0.0127)	(0.0147)	(0.0163)	(0.0192)	(0.0273)	(0.0273)
Observations	805	805	805	805	805	805	805
R-squared	0.052	0.034	0.022	0.033	0.028	0.040	0.040

Notes: Regression results based on an ongoing survey examining Covid-19 in nursing homes. Using retrospective questions on robot adoption, we examine whether nursing homes that adopt robots over one year see a significant change in the case mix of residents, as measured by the share of residents of different care-required levels. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table 8. Staffing regression results when controlling for the number of different types of services provided by the nursing home

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All employees			Regular employees			Non-regular employees		
VARIABLES	Log(number of care workers)	Log(number of nurses)	Log(total number of employees)	Log(number of care workers)	Log(number of nurses)	Log(total number of employees)	Log(number of care workers)	Log(number of nurses)	Log(total number of employees)
Adopt robots	0.234**	0.378***	0.277***	-0.0790	0.0583	0.00317	0.942***	0.652***	0.763***
	(0.0963)	(0.106)	(0.0952)	(0.116)	(0.0828)	(0.112)	(0.183)	(0.228)	(0.138)
Observations	857	857	857	857	857	857	857	857	857
R-squared	0.449	0.377	0.459	0.430	0.377	0.443	0.024	0.057	0.216

Notes: 2SLS results that additionally includes 41 dummies representing the different services provided by nursing homes. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table 9. Robot adoption and staffing by type and time - OLS results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Log(number of care workers)			Log(number of nurses)			Log(total number of employees)
	All employees	Regular employees	Non-regular employees	All employees	Regular employees	Non-regular employees	
Panel A. Adoption by type of robot							
Aid robots	0.0146	-0.0134	0.0973	0.0598	0.000149	0.159**	0.0427
	(0.0554)	(0.0679)	(0.0913)	(0.0543)	(0.0634)	(0.0791)	(0.0575)
Mobility robots	-0.00669	0.0211	-0.0768	-0.0251	0.0168	0.00508	-0.0295
	(0.0599)	(0.0654)	(0.114)	(0.0658)	(0.0643)	(0.100)	(0.0608)
Montoring and communication robots	0.0351	0.0356	0.0437	0.0466	0.0814*	-0.0804	0.0403
	(0.0381)	(0.0452)	(0.0625)	(0.0344)	(0.0425)	(0.0616)	(0.0413)
Observations	857	857	857	857	857	857	857
R-squared	0.429	0.408	0.254	0.505	0.476	0.217	0.385
Panel B. Adoption by time							
Robot first adopted before 2017	0.0334	0.0123	0.0860	0.0573*	0.0619	0.0507	0.0430
	(0.0348)	(0.0428)	(0.0582)	(0.0330)	(0.0377)	(0.0546)	(0.0377)
Robot first adopted in 2017	0.103	0.150**	0.0216	0.137**	0.119	-0.0272	0.145**
	(0.0693)	(0.0675)	(0.132)	(0.0623)	(0.0861)	(0.123)	(0.0717)
Observations	857	857	857	857	857	857	857
R-squared	0.430	0.410	0.254	0.507	0.477	0.213	0.387
Base facility characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Resident case-mix	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other technology adoption	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Management practices	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HR development practices	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Labor shortage perceptions	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Base facility characteristics control for years of operation, location (metropolis, urban, rural), corporation type, region fixed effects (we divide Japan into 6 regions), and skilled nursing homes. Resident case-mix controls for the log number of residents with care levels 1-3, 4, and 5. Other technology adoption controls for each non-robot technology used in the nursing homes. Management practices control for human resource management practices. Prefecture characteristics controls for the demographic and economic conditions. HR development practices control for human resource development practices in a facility. Labor shortage perceptions control for labor shortage perceptions on careworkers, nurses, and laborers in general. Standard errors clustered by prefecture are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 10. Robot adoption and wage by type and time - OLS results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Care workers				Nurses				Managers
	All employees		Regular employees	Non-regular employees	All employees		Regular employees	Non-regular employees	
VARIABLES	Log(monthly wage)	Log(hourly wage)	Log(monthly wage)	Log(hourly wage)	Log(monthly wage)	Log(hourly wage)	Log(monthly wage)	Log(hourly wage)	Log(monthly wage)
Panel A. Adoption by type of robot									
Aid robots	0.00453	0.0204	0.00150	0.0203	-0.0363	-0.0109	-0.0334	-0.0136	0.0798*
	(0.0226)	(0.0148)	(0.0216)	(0.0147)	(0.0221)	(0.0435)	(0.0219)	(0.0446)	(0.0452)
Mobility robots	-0.0198	-0.00260	-0.0178	-0.00265	0.00681	0.0246	0.00568	0.0370	-0.0661
	(0.0210)	(0.0217)	(0.0210)	(0.0217)	(0.0164)	(0.0350)	(0.0159)	(0.0395)	(0.0579)
Monitoring and communication robots	-0.00262	-0.0170	-0.00250	-0.0168	-0.00146	-0.095**	-0.00502	-0.11***	-0.0231
	(0.0133)	(0.0138)	(0.0125)	(0.0136)	(0.0121)	(0.0360)	(0.0122)	(0.0354)	(0.0282)
Observations	6,805	1,685	6,360	1,674	1,307	202	1,251	196	650
R-squared	0.590	0.316	0.569	0.316	0.508	0.798	0.467	0.799	0.429
Panel B. Adoption by time									
Robot first adopted before 2017	-0.00846	-0.0157	-0.00867	-0.0151	-0.0111	-0.065**	-0.0128	-0.068**	-0.00793
	(0.0141)	(0.0114)	(0.0138)	(0.0112)	(0.0150)	(0.0311)	(0.0143)	(0.0312)	(0.0360)
Robot first adopted in 2017	0.0154	-0.00167	0.0112	-0.00273	-0.00969	-0.0412	-0.0176	-0.0529	0.0391
	(0.0292)	(0.0187)	(0.0299)	(0.0189)	(0.0285)	(0.0500)	(0.0319)	(0.0553)	(0.0645)
Observations	6,805	1,685	6,360	1,674	1,307	202	1,251	196	650
R-squared	0.590	0.315	0.569	0.315	0.507	0.791	0.466	0.790	0.426
Worker characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Base facility characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Resident case-mix	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other technology adoption	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Management practices	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HR development practices	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Labor shortage perceptions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Base facility characteristics control for years of operation, location (metropolis, urban, rural), corporation type, region fixed effects (we divide Japan into 6 regions), and skilled nursing homes. Resident case-mix controls for the log number of residents with care levels 1-3, 4, and 5. Other technology adoption controls for each non-robot technology used in the nursing homes. Management practices control for human resource management practices. Prefecture characteristics controls for the demographic and economic conditions. HR development practices control for human resource development practices in a facility. Labor shortage perceptions control for labor shortage perceptions on careworkers, nurses, and laborers in general. Standard errors clustered by prefecture are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 11. Robot adoption and care worker turnover

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All workers			Regular workers			Non-regular workers		
	Separation rate	Hiring rate	Turnover rate	Separation rate	Hiring rate	Turnover rate	Separation rate	Hiring rate	Turnover rate
Panel A. OLS estimates									
Adopt robots	-0.0153	-0.00667	-0.0219	-0.0129	-0.00780	-0.0207	0.00378	0.0259	0.0296
	(0.00985)	(0.0116)	(0.0192)	(0.00918)	(0.0115)	(0.0177)	(0.0212)	(0.0245)	(0.0402)
Observations	779	779	779	776	776	776	756	756	756
R-squared	0.095	0.132	0.120	0.147	0.136	0.158	0.074	0.100	0.097
Panel B. 2SLS estimates									
Adopt robots	-0.0433	-0.0458	-0.0890	0.00165	-0.0691*	-0.0674	0.0389	0.104	0.143
	(0.0787)	(0.0439)	(0.111)	(0.0453)	(0.0409)	(0.0747)	(0.100)	(0.0801)	(0.147)
Observations	779	779	779	776	776	776	756	756	756
First stage F-statistic	41.922	41.922	41.922	44.499	44.499	44.499	40.265	40.265	40.265
Base facility characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Resident case-mix	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other technology adoption	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Management practices	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HR development practices	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Labor shortage perceptions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Base facility characteristics control for years of operation, location (metropolis, urban, rural), corporation type, region fixed effects (we divide Japan into 6 regions), and skilled nursing homes. Resident case-mix controls for the log number of residents with care levels 1-3, 4, and 5. Other technology adoption controls for each non-robot technology used in the nursing homes. Management practices control for human resource management practices. Prefecture characteristics controls for the demographic and economic conditions. HR development practices control for human resource development practices in a facility. Labor shortage perceptions control for labor shortage perceptions on careworkers, nurses, and laborers in general. Standard errors clustered by prefecture are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 12. IV results by robot type

VARIABLES	(1) Log(number of care workers)	(2) Log(number of nurses)	(3) Log(total number of employees)
Panel A. Regular employees			
Monitoring and communication robots	-0.113	-0.00119	-0.0605
	(0.173)	(0.167)	(0.194)
Observations	857	857	857
First stage F-statistic	63.404	63.404	63.404
Transfer aid robots	-0.216	-0.00228	-0.115
	(0.337)	(0.318)	(0.374)
Observations	857	857	857
First stage F-statistic	58.172	58.172	58.172
Mobility robots	-0.395	-0.00417	-0.212
	(0.617)	(0.583)	(0.688)
Observations	857	857	857
First stage F-statistic	7.989	7.989	7.989
Panel B. Non-regular employees			
Monitoring and communication robots	1.538***	1.135***	1.100***
	(0.262)	(0.378)	(0.225)
Observations	857	857	857
First stage F-statistic	63.404	63.404	63.404
Transfer aid robots	2.936***	2.168***	2.101***
	(0.601)	(0.656)	(0.503)
Observations	857	857	857
First stage F-statistic	58.172	58.172	58.172
Mobility robots	5.380**	3.972**	3.849***
	(2.264)	(1.859)	(1.375)
Observations	857	857	857
First stage F-statistic	7.989	7.989	7.989

Notes: Worker characteristics control for gender, age, age squared, experience, experience squared, and qualification level of the worker. Base facility characteristics control for years of operation, location (metropolis, urban, rural), corporation type, region fixed effects (we divide Japan into 6 regions), and skilled nursing homes. Resident case-mix controls for the log number of residents with care levels 1-3, 4, and 5. Other technology adoption controls for each non-robot technology used in the nursing homes. Management practices control for human resource management practices. Prefecture characteristics controls for the demographic and economic conditions. HR development practices control for human resource development practices in a facility. Labor shortage perceptions control for labor shortage perceptions on careworkers, nurses, and laborers in general. Standard errors clustered by prefecture are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 12. Robot adoption and staffing – IV Estimates using 2016 instrumental variable

	(1)	(2)	(3)
VARIABLES	Log(number of care workers)	Log(number of nurses)	Log(total number of employees)
Panel A. All employees			
Adopt robots	0.320***	0.427***	0.380***
	(0.103)	(0.135)	(0.133)
Observations	857	857	857
First stage F-statistic	51.556	51.556	51.556
Panel B. Regular employees			
Adopt robots	-0.0274	-0.0909	0.0472
	(0.148)	(0.135)	(0.167)
Observations	857	857	857
First stage F-statistic	51.556	51.556	51.556
Panel C. Non-regular employees			
Adopt robots	1.005***	0.849***	0.879***
	(0.220)	(0.281)	(0.185)
Observations	857	857	857
First stage F-statistic	51.556	51.556	51.556
Base facility characteristics	Yes	Yes	Yes
Resident case-mix	Yes	Yes	Yes
Other technology adoption	Yes	Yes	Yes
Management practices	Yes	Yes	Yes
Prefecture characteristics	Yes	Yes	Yes
HR development practices	Yes	Yes	Yes
Labor shortage perceptions	Yes	Yes	Yes

Appendix Table 13. Robot adoption and staffing – IV Estimates (Custodial nursing homes only)

	(1)	(2)	(3)
VARIABLES	Log(number of care workers)	Log(number of nurses)	Log(total number of employees)
Panel A. All employees			
Adopt robots	0.328***	0.590***	0.230
	(0.120)	(0.166)	(0.146)
Observations	684	684	684
First stage F-statistic	26.499	26.499	26.499
Panel B. Regular employees			
Adopt robots	-0.127	0.0262	-0.134
	(0.150)	(0.155)	(0.176)
Observations	684	684	684
First stage F-statistic	26.499	26.499	26.499
Panel C. Non-regular employees			
Adopt robots	1.210***	1.033***	0.734***
	(0.203)	(0.381)	(0.198)
Observations	684	684	684
First stage F-statistic	26.499	26.499	26.499
Base facility characteristics	Yes	Yes	Yes
Resident case-mix	Yes	Yes	Yes
Other technology adoption	Yes	Yes	Yes
Management practices	Yes	Yes	Yes
Prefecture characteristics	Yes	Yes	Yes
HR development practices	Yes	Yes	Yes
Labor shortage perceptions	Yes	Yes	Yes

Notes: Worker characteristics control for gender, age, age squared, experience, experience squared, and qualification level of the worker. Base facility characteristics control for years of operation, location (metropolis, urban, rural), corporation type, region fixed effects (we divide Japan into 6 regions), and skilled nursing homes. Resident case-mix controls for the log number of residents with care levels 1-3, 4, and 5. Other technology adoption controls for each non-robot technology used in the nursing homes. Management practices control for human resource management practices. Prefecture characteristics controls for the demographic and economic conditions. HR development practices control for human resource development practices in a facility. Labor shortage perceptions control for labor shortage perceptions on careworkers, nurses, and laborers in general. Standard errors clustered by prefecture are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 14. Robot adoption and staffing – IV Estimates (Using dummies for perception variables)

	(1)	(2)	(3)
VARIABLES	Log(number of care workers)	Log(number of nurses)	Log(total number of employees)
Panel A. All employees			
Adopt robots	0.304***	0.349***	0.264**
	(0.0703)	(0.121)	(0.110)
Observations	859	859	859
First stage F-statistic	80.383	80.383	80.383
Panel B. Regular employees			
Adopt robots	-0.0248	0.0852	0.0168
	(0.102)	(0.110)	(0.124)
Observations	859	859	859
First stage F-statistic	80.383	80.383	80.383
Panel C. Non-regular employees			
Adopt robots	1.087***	0.626**	0.721***
	(0.178)	(0.269)	(0.164)
Observations	859	859	859
First stage F-statistic	80.383	80.383	80.383
Base facility characteristics	Yes	Yes	Yes
Resident case-mix	Yes	Yes	Yes
Other technology adoption	Yes	Yes	Yes
Management practices	Yes	Yes	Yes
Prefecture characteristics	Yes	Yes	Yes
HR development practices	Yes	Yes	Yes
Labor shortage perceptions	Yes	Yes	Yes

Appendix Table 15. Robot adoption and staffing – IV Estimates (Using both dummies and leave-one-out variables for perception variables)

	(1)	(2)	(3)
VARIABLES	Log(number of care workers)	Log(number of nurses)	Log(total number of employees)
Panel A. All employees			
Adopt robots	0.246***	0.381***	0.213*
	(0.0796)	(0.118)	(0.114)
Observations	857	857	857
First stage F-statistic	75.273	75.273	75.273
Panel B. Regular employees			
Adopt robots	-0.0968	0.0381	-0.0684
	(0.123)	(0.115)	(0.139)
Observations	857	857	857
First stage F-statistic	75.273	75.273	75.273
Panel C. Non-regular employees			
Adopt robots	0.997***	0.722***	0.690***
	(0.160)	(0.257)	(0.159)
Observations	857	857	857
First stage F-statistic	75.273	75.273	75.273
Base facility characteristics	Yes	Yes	Yes
Resident case-mix	Yes	Yes	Yes
Other technology adoption	Yes	Yes	Yes
Management practices	Yes	Yes	Yes
Prefecture characteristics	Yes	Yes	Yes
HR development practices	Yes	Yes	Yes
Labor shortage perceptions	Yes	Yes	Yes